



Radical timetable innovations in long-distance railway passenger transport: How might these affect railway passenger demand?

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ARTICLE INFO

Keywords:

Integrated periodic timetable (IPT)
Long-distance railway transport
Railway passenger demand
Railway network

ABSTRACT

The positive impact of coordinated timetable innovations throughout national railway networks has been shown exemplarily in the 1970 s and 80 s, when so-called integrated periodic timetables (IPT) were installed in the Netherlands and in Switzerland and then gradually improved. After large-scale changes of the former train offer, rail passenger demand increased significantly. A similar timetable innovation was recently decided for the German railway network. However, the project's impact on overall demand is uncertain. To approach this question, an elasticity-based forecast of long-distance passenger demand is proposed and adopted to a modeled railway network section that has changed to an IPT. Massive travel time reductions turned out as the most important factor for demand growth followed by demand effects due to the increase of train frequency and changes of a modeled ticket price system. Additional factors influencing nationwide rail passenger demand are conceivable but difficult to generalize.

1. Introduction

Investigation of passenger demand in regional and long-distance railway transportation systems tends to be a marginalized subject of research since only little evidence is recorded in scientific literature. This seems even more true if the focus is not only on railway transport but on specific timetable aspects. Characterized by travel times, train frequency and need for transfers, timetables combine factors that are particularly relevant for travel mode decisions. It was notably in the Netherlands and Switzerland where large-scale national timetable improvements have been initiated to encourage rail passenger demand significantly (Avelino et al., 2006). The common idea in both countries was to coordinate train runs within the network and then, to realize short transfers at all transfer-relevant nodes. Periodicity and time symmetry turned out to be essential for what is called “integrated periodic timetable” (IPT). Whereas periodicity of train runs is a relatively simple planning task meaning that each train line is served by fixed time intervals, requirements increase significantly when train arrivals and departures are to be installed symmetrically, which is usually around full and half hours (SMA and Partner, 2021).

Implementation of IPTs both in the Netherlands and Switzerland was followed by a growth in passenger demand. Anyhow, the concept has not yet been transferred to other large national railway networks, partly

as it was considered as too complex. It was in 2013 when Germany changed its position and announced its willingness to establish a network-wide IPT *Deutschlandtakt* within some decades connected with political expectation of doubling passenger numbers within very few years (CDU, CSU, SPD, 2013). The subject of an IPT has therefore become relevant in railway transport politics. However, from a scientific point of view, it remains unclear whether rail passenger demand can reach the politically desired scale and to what extent single measures will contribute to an overall increase in demand. Regarding the actuality of the topic, it is worth examining IPTs more closely from today's perspective. Within this paper, forecast of long-distance railway passenger transport is proposed based on elasticities of travel demand. The focus lies on three demand elasticities “travel time”, “ticket prices” and “train frequency”. By referring to published elasticity values for railway transport within the UK, Switzerland and Germany, forecast scenarios are built reflecting a range of possible changes in passenger reactions. This forecasting approach is then adopted to a modeled railway network that has changed to an IPT. In accordance with objectives of the *Deutschlandtakt*, transition from Non-IPT to IPT includes major reductions in travel time, increased train frequency and changes in the tariff system. The model network is designed representing – albeit highly abstracted – the situation of long-distance passenger transport in northern Germany with Hannover as a central-located node. Network

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<https://doi.org/10.1016/j.jpuptr.2024.100090>

Received 30 October 2023; Received in revised form 19 April 2024; Accepted 23 April 2024

Available online 30 April 2024

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topology should enable calculating numerous transfer possibilities between five long-distance railway lines running through this node. According to the model environment, relative changes of travel times, train frequency and ticket prices are to be calculated and applied to the elasticity-based forecast of passenger demand. Altogether, passenger demand calculation is elaborated for about 80 source-target relations with travel distances between approximately 100 and 500 kilometers. The model should provide results both for the entire railway network and for single rail lines. By referring to the model output, several research questions regarding railway passenger demand after network-wide IPT introductions are to be answered.

2. Research for reference values for the elasticity of railway travel demand

2.1. Explanation of the forecasting approach

If an IPT concept *Deutschlandtakt* is considered, the question arises whether demand effects can be reliably forecasted. Regional- and long-distance railway transport is rather seldomly focused in scientific literature. Studies of travel choice decisions for railways, notably elaborated in the United Kingdom (UK), often refer to external or socio-economic factors that contribute to rail use or prevent it (see e.g. [Blainey et al., 2012](#); [ITS et al., 2016](#); [Williams and Jahanshahi, 2018](#)). However, apart from socio-economic or external factors, attributes focused within an IPT, thereof “interchange”, “service frequencies” and “travel time”, are still judged to be relevant to changes in rail travel demand. Nevertheless, concentration on socio-economic or external demand factors in discrete travel models weakens the relevance of timetable-based factors. Findings which are relatively extensive for the UK are not necessarily transferable to other countries. Other studies focus on high-speed trains (HST) only. For this market segment, it turns out very clearly that demand is extremely sensitive to timetabling and pricing (see e.g. [Behrens and Pels, 2012](#); [Cascetta and Coppola, 2015](#); [Gundelfinger-Casar and Coto-Millán, 2017](#)). Apart from several research activities in the UK, data deficiency is identified for the rail passenger market outside HST. Taking all these points together, the authors’ decision is not referring to one discrete travel model but calculating possible demand reactions within an IPT more illustratively by using different magnitudes of demand elasticities. Demand elasticities are typically derived from discrete choice models using Revealed Preferences (RP) or Stated Preferences (SP) survey data (see e.g. [Wardman, 2022a](#)). Demand elasticities therefore reflect the responsiveness of discrete choice models. Typical magnitudes and value ranges of demand elasticities are researched in literature (chapter 2.2) and then selected for our own forecasting approach (chapter 2.3). These values are incorporated into our model algorithm described in chapter 3.2.

Usage of demand elasticities is accepted for network-wide, strategic planning tasks, as it is stated by [Wardman \(2022a\)](#). In general, the elasticity approach leads to massive simplification of complex demand patterns but is regarded as very helpful to make demand potentials of a well-established IPT comprehensible. In general, the elasticity is defined as follows (Equation 1; [Sievering, 2021](#)).

$$\varepsilon = \frac{\text{relative change of the effect}}{\text{relative change of the cause}} [-]$$

Equation 1: General definition of the elasticity

One elasticity widely used in economics is the price elasticity of demand, which is determined as follows ([Sievering, 2021](#)) (Equation 2). It indicates the extent to which price changes (the cause) are accompanied by changes in quantity. In the case of negative ε_p , an increase in price (positive Δp) is accompanied by a decrease in demand (negative Δx). Conversely, a price reduction ensures an increase in demand (positive ε_p). Demand elasticity shown for prices can be defined in the same way for the attribute “travel time” (Equation 3) and for the attribute “train frequency” (Equation 4).

$$\varepsilon_p = \frac{\text{relative change in demand}}{\text{relative change in prices}} = \frac{(\Delta x/x)}{(\Delta p/p)} [-]$$

Equation 2: Definition of the demand elasticity for price changes

$$\varepsilon_t = \frac{\text{relative change in demand}}{\text{relative change in travel time}} = \frac{(\Delta x/x)}{(\Delta t/t)} [-]$$

Equation 3: Definition of demand elasticity for travel time changes

$$\varepsilon_f = \frac{\text{relative change in demand}}{\text{relative change in frequency}} = \frac{(\Delta x/x)}{(\Delta f/f)} [-]$$

Equation 4: Definition of the demand elasticity for frequency changes

In the field of public transport economics, most studies focus on demand elasticities for “prices” and “travel time” and relate changes in quantity to the modal split. The modal split is quantified by shares of the traffic volume (trips). Demand elasticities for the attributes “headway” respectively “train frequency”, “train delays” and “transfers” have been determined very rarely so far. However, a detailed consideration of transfer times and their effect on demand would be particularly interesting. To the authors’ knowledge, it has not yet been possible to empirically differentiate passenger-related perception of transfers in long-distance railway transport from other demand attributes. Still, there are findings regarding travelers’ perception of transfer situations, especially in local transportation (see e.g. [Garcia-Martinez et al., 2018](#) or [Iseki and Taylor, 2009](#)). It becomes clear that unfavorable transfer situations influence the perception of transfers negatively. Conversely, perception of transfers can be improved if transfer times and walking distances are shortened, for example. Unfortunately, there are practically no reliable and quantifiable findings on how travelers in long-distance railway transport react to various transfer situations. This is something that also [Wardman \(2022a\)](#) noted while conducting a meta-study on elasticities of demand in railway transport. Due to the data situation given, we cannot apply specific elasticities for the transfer time. Also, application of transfer penalties stated in literature (see e.g. [Iseki and Taylor, 2009](#)) seems not suitable for an IPT in railways with particularly short and well-established transfers. Since current findings do not provide enough evidence for a detailed quantification of demand potential following transfer optimization, modeling of transfers in our approach concentrates on variation of transfer times only. Direct connections remain as such; the same applies to transfer connections. Further transfer aspects (e. g. walking distances, comfort, security) are considered unchanged. Effects of shortened transfer times will then be included within travel time elasticities.

2.2. Research for current elasticities of railway-related travel

Current scientific research on elasticities of railway-related travel concentrates on the UK ([Wardman, 2022a, 2022b](#)). Extensive meta-analyses provide mean elasticity values for the attributes “travel time”, “headway” and “prices”, further subdivided by travel purposes (TP) and spatial categories (SC) ([Table 1](#)). Accordingly, business travelers are more sensitive to travel time than leisure travelers whereas demand for inter-urban travel is more time-sensitive than for urban or suburban travel. Headway or train frequency elasticity has relatively low absolute values. It can be stated that for inter-urban travel, train frequency is slightly less relevant for demand compared to urban or suburban travel. Regarding price elasticity, leisure travelers are much more price-sensitive than business travelers. In contrast, there are hardly any price elasticity differences between shorter and longer distances within the UK. The price elasticity is the largest in terms of absolute values, followed by travel time elasticity and finally, headway.

Published elasticities of travel demand within the EU, especially for long-distance railway transport, are quite rare. [Nordenholz et al. \(2016\)](#) recorded elasticities for German “travel time” and “costs” to estimate

Table 1

Elasticity parameters for public passenger transport from British studies mainly related to rail (various sources).

attribute	British demand elasticities (UK)				
	all TP and SC (rail-related)	TP „business“ (all modes)	TP „leisure“ (all modes)	SC „(sub)urban“ (all modes)	SC „inter-urban“ (all modes)
travel time	– 0.71	– 0.63 ^a	– 0.56 ^a	– 0.54 ^a	– 0.69 ^a
frequency / headway	– 0.25			– 0.41 ^b	– 0.25 ^b
		TP „business“ (rail-related)	TP „leisure“ (rail-related)	SC „(sub)urban“ (rail-related)	SC „inter-urban“ (rail-related)
costs / prices ^c		– 0.58	– 0.98	– 1.01	– 1.10

Sources: for travel time and headway: Wardman (2022a); for prices: Wardman (2022b)

^a Mean values were recorded mainly (57%) from rail-related observations, but also from car (30%) and bus (13%) as means of transport. Purely rail-related values were not published for various TP and SC.

^b Mean values were recorded mainly (65%) from rail-related observations, but also from bus (35%) as means of transport. Purely rail-related values were not published for various SC.

^c Values were recorded exclusively from rail-related observations, metros included. Values for travel purposes refer to another sample as those for spatial categories.

demand effects for long-distance rail passenger transport. Apart from that, study situation is not satisfactory. Regarding Switzerland, elasticities of travel demand are available from the year 2015 depending on distance (Weis et al., 2017). Following Wardman's differentiation into travel purposes "business" and "leisure", Swiss values for business trips (so-called "commercial travel") and leisure trips (so-called "private travel") are singled out. In Switzerland, the elasticity increases as the length of trips increases whereas German values were published as mean values over distances (Table 2). The indicators collected for Germany show rather low magnitudes, especially when compared with Swiss values. The Swiss travel time elasticity of commercial travel is more than three times as large as that of German business travel. Also, the time elasticity for private travel is significantly higher in Switzerland than in Germany. Generally speaking for both countries and trip purposes, the travel time factor is larger than the travel costs factor - and this is something that has not been observed in British elasticities. In the case of cost elasticity, Swiss values again are significantly higher than German ones (Table 2).

2.3. Determination of elasticity values of travel demand for own calculations

In coherence to elasticity values published, we want to concentrate our model calculations on three elasticities "travel time", "train

Table 2

Elasticity parameters for long-distance rail passenger transport from German and Swiss studies (various sources).

attribute	German long-distance rail transport demand elasticities (DE)		Swiss long-distance public transport demand elasticities (CH)	
	TP „business“	TP „leisure“	TP „commercial“ ^a	TP „private“ ^a
travel time	– 0.52	– 0.71	– 1.78	– 1.13
costs / prices	– 0.31	– 0.57	– 0.73	– 0.95

Sources: for Germany (DE): Nordenholz et al. (2016); for Switzerland (CH): Weis et al. (2017)

^a Values were recorded for a travel distance of 100 kilometers.

frequency" (respectively "headway") and "costs" (respectively "prices"). By doing so, demand effects of an IPT-typical reduction of travel times, shortening of transfer times, increase of train frequency and changes to the ticket price system are to be examined illustratively. Two different scenarios are built to reflect a range of possible changes in passenger reactions. Both scenarios differentiate between elasticities for the travel purpose "business" as well as "leisure". One first calculation should base on constant travel time and price elasticities across all travel distances (ϵ constant). The value of constant travel time and price elasticities is based on elasticities determined for Germany by Nordenholz et al. (2016). Usage of German elasticity values should stand for a rather restrained demand forecast. The second calculation is made analogous to the Swiss findings, i.e. elasticity increases in amount with increasing travel distance (ϵ variable). This approach is intended to account not only for "travel time" but also for "ticket prices". The minimum elasticity value should refer to travel distances up to 100 km, the maximum value is used for distances of 500 km and more. Linear interpolation is used for intermediate distances and refers to a more optimistic forecast that assumes passenger behavior as for the Swiss population determined by Weis et al. (2017). An overview of the elasticity values used for travel time and price is given below (Table 3).

Changes in demand due to changes in frequency should be modeled with elasticity values that are in the order of values recorded by Wardman (2022a), at least if a doubling of frequency from 120 to 60 minutes or 60 to 30 minutes is regarded. If frequency is adjusted from 30 to 15 minutes, the demand reaction is considered as less elastic compared to Wardman. It is assumed that business travelers react somewhat more sensitive to changes in frequency than leisure travelers. An overview of the elasticity values used for headway is provided below (Table 4).

3. Rail passenger demand forecast within an exemplary railway network section

As mentioned in the introduction part, central characteristics of an IPT as also intended with the *Deutschlandtakt* should be transferred to a modeled railway network section, followed by an elasticity-based forecast of passenger demand. These characteristics are increased train frequency, travel time reductions and a shortening of transfer times. As it is explained later, changes to the ticket price system will also be considered. In the following, we describe the model environment starting with the network topology and its baseload (chapter 3.1.1). Then, different stages of the network's timetable will be defined (chapter 3.1.2) and the network's tariff system is explained (chapter 3.1.3). These steps correspond to the left part of the process diagram shown below (Fig. 1).

The actual model algorithm for the calculation of passenger demand is presented in chapter 3.2. It requires as input parameters percentual changes of travel times and ticket prices as well as changes in train frequency. Also, elasticity values of travel demand determined in chapter 2.3 and the network's baseload in terms of passengers transported are required (Fig. 1). The model is designed to determine changes in demand for the entire network as well as per train line. The following

Table 3

Range of "travel time" and "costs / "prices" elasticity values used for own calculations.

attribute	ϵ constant constant elasticity values for all travel distances		ϵ variable variable elasticity values depending on travel distance	
	TP business	TP leisure	TP business	TP leisure
travel time	– 0.52	– 0.71	min. – 0.55 max. – 1.75	min. – 0.70 max. – 1.10
costs / prices	– 0.31	– 0.57	min. – 0.30 max. – 0.70	min. – 0.55 max. – 0.95

Table 4

Range of „headway” / “frequency” elasticity values used for own calculations.

attribute	Headway elasticities depending on the scope of timetable changes					
	$\varepsilon_{120 \rightarrow 60}^a$		$\varepsilon_{60 \rightarrow 30}^b$		$\varepsilon_{30 \rightarrow 15}^c$	
	TP business	TP leisure	TP business	TP leisure	TP business	TP leisure
headway / frequency	- 0.30	- 0.25	- 0.20	- 0.15	- 0.10	- 0.05

^a $\varepsilon_{120 \rightarrow 60}$: elasticity used for timetable changes from 120-minutes-intervals to 60-minutes-intervals.

^b $\varepsilon_{60 \rightarrow 30}$: elasticity used for timetable changes from 60-minutes-intervals to 30-minutes-intervals.

^c $\varepsilon_{30 \rightarrow 15}$: elasticity used for timetable changes from 30-minutes-intervals to 15-minutes-intervals.

questions should particularly be answered, which is done in chapter 3.3.

- (1) How does the network-wide increase in train-kilometers in the IPT scenarios relate to the increase in passenger demand?
- (2) What is the variation span of travel time, frequency and cost related effects on passenger demand across all source-target relations within the network?
- (3) How does growth rates in passenger demand differ depending on whether source-target relations are directly connected or include need for interchanges?
- (4) How does the average seat occupancy rate per train line change and how is this related to travel time, frequency and cost effects?

3.1. Characteristics of the modeled railway network section

3.1.1. Definition of the network section's topology and its baseline

The modeled railway network section is built on the idea of being able to represent conditions of the planned *Deutschlandtakt* as well as characteristics of an ideal typical IPT. Network's topology should represent long-distance passenger train lines bundling traffic flows over sections about more than 100 kilometers, as it is often the case in Germany and other large-scale European countries. These railway lines run

radially towards a railway node called “A” that is centrally located. Based on this network topology, five long-distance passenger train lines are planned to connect source-target relations in a distance range from 100 to 500 kilometers. A blue line runs I-A-E, two red lines are designed with alternating directions D-A-H or D-A-G, respectively. A green line runs diagonal C-A-F and a violet line runs B-A-E and, for section A-E, shares the same rail infrastructure as the blue line (Fig. 2). The topology of this railway network is inspired from the existing situation in northern Germany with Hannover as a central-located node for long-distance travelers, but as already argued, a highly abstracted representation was made.

The existence of numerous transfer possibilities within the modeled railway node “A” does not mean that all of them are equally relevant in terms of utilization. As in reality, it is supposed that demand for some of the transfers is to a certain extent minimized thanks to transfer-free train connections outside the modeled network section. For example, it is supposed that transfer-free and faster connections are possible between I-B, B-C, C-D etc. without the need for traveling via “A”. In contrast, demand for transfers is notably assumed for connections between the violet and green line (e. g. B-A-F), the green and blue line (e. g. C-A-E) as well as for some connections using the blue and red line (e. g. I-A-D).

It is now important to notice that different assumptions are made

Network design in compliance to an ideal IPT

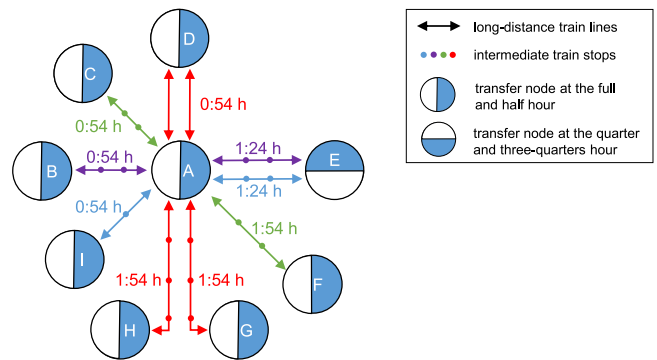
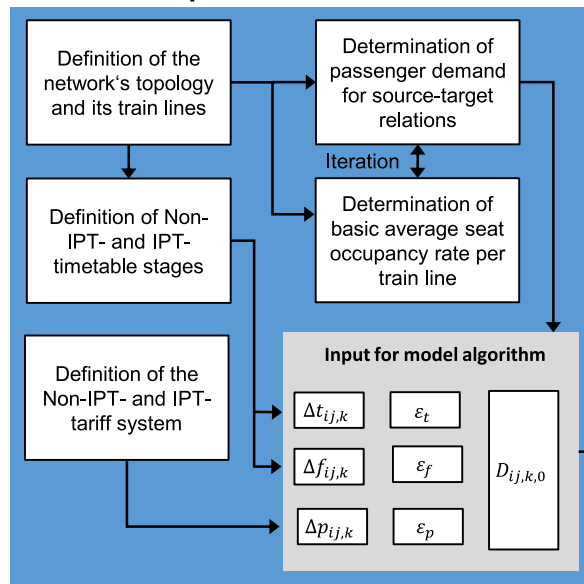


Fig. 2. Topology of the modeled railway network section.

Model development



Model application

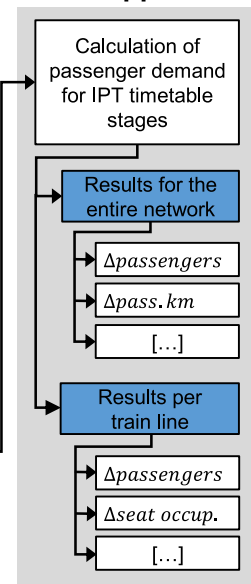


Fig. 1. Simplified presentation of successive steps for model development and application.

regarding the revenue-relevance of passenger lines represented in the network. The blue line I-A-E, the violet line B-A-E as well as connections on the red line D-A-H are supposed to bundle strong demand. This means that an average seat occupancy rate of approx. 70% is assumed across all annual operating trains. Seat capacity per train is approximately oriented to German ICE- and IC-trains. It is for sure that 70% seat occupancy is a high average load factor, but in recent past (COVID-19 excluded) not unusual in long-distance train connections between German metropolitan regions as Berlin, Cologne / Rhine-Ruhr, Frankfurt / Rhine-Mine, Hamburg or Munich. It is also true that high average seat occupancy rates over the entire year include overbooking, e. g. during vacation periods, which is also reality in Germany. Apart from connections between metropolitan regions, the country knows large areas with lower population densities that are also connected to long-distance transport. Rail traffic on less revenue-relevant connections is represented by the green line C-A-F where average seat occupancy is defined to 55% across all trains a year.

Regarding the origin of traffic within the network, assumptions are made to deal with complexity. For all nodes “A” to “I”, a long-distance passenger traffic volume resulting from the wider perimeter of this node as well as from passengers passing through this node is determined. The traffic volume is further divided into work-related and leisure-related trips. In coherence to the assumptions that blue and red lines connect economic prosperous metropolitan areas, a relatively high share of work-related trips (up to 40%) is defined there. In contrast, a clear dominance of leisure-related trips (up to 85%) is defined for the green and violet line. For each of the nodes “A” to “I”, passenger volume as well as the distribution of volumes to source-target-relations were adjusted iteratively. The goal of the iteration process was on the one hand to achieve the average seat occupancy rates described above. Second criterion was to differentiate the varying importance of transfers in “A” for the passengers of one line. It is assumed that about 25% of daily passengers using the red lines and about 30% using the blue line are obliged to transfer to another line in “A”. In contrast, for the violet and especially for the green line, it is about 50% and 75%. Some of the basic assumptions are summarized below (Table 5). Basic passenger demand per source-target relation is provided in the appendix (Table 12).

3.1.2. Definition of the network's timetables

As mentioned at the beginning of the paper, characteristics of an IPT concept, namely increase of train frequency, reduction of travel times and a shortening of transfer times, should serve for passenger demand calculations within our model. These are now to be transferred into exemplary timetable structures.

A first timetable should correspond to the state *before* the implementation of an IPT and is called “Non-IPT”. Determination of train frequency comprises 60-minutes-intervals for the red, blue and green line and 120-minutes-intervals for the violet one. In view of the network section A-D which is used by both red lines D-A-G and D-A-H, it is assumed that optimal temporal distribution of trains is resulting in a 30-minutes-interval there. This so-called “line bundling” leads to higher train frequency only at short network sections regarded as especially

revenue relevant. Based on the 60- and 120-minutes-intervals within the Non-IPT, halving to 30- and 60-minutes-intervals is modeled in the case of the IPT. The IPT if further subdivided into a first stage (IPT 1), where 30-minutes-intervals are limited to the I-A-E axis, and a second stage (IPT 2), where 30-minutes-intervals are also introduced at the D-A-H and D-A-G axis (Table 6).

The Non-IPT corresponds to the state before the implementation of an IPT concept, which means that train arrivals and departures do not take place according to strictly defined time symmetries. Still, the Non-IPT is not intended to represent a worst-case scenario and thus the unlikely case of a complete lack of transfer planning. Instead, a transfer situation is reflected which is characterized by heterogeneity including very long (> 20 minutes), medium (10–20 minutes) as well as short (< 10 minutes) transfer times. Reflecting this time heterogeneity, the Non-IPT is calculated with planned transfer times in a time span between 8 and about 60 minutes. In the latter case, connection trains are missed by a very small margin. Passengers then are forced to wait a full train frequency-interval for connections.

In the two IPTs (IPT 1 and IPT 2), *ideal* connections between train-services should be modeled within the central node “A”. Therefore, symmetry time is defined at half and full hours for most of the train runs. For half of the trains circulating at the red lines D-A-G and D-A-H, a secondary symmetry is established at the quarter and three-quarters hour. Transfer times between long-distance trains are set to 6 minutes for each direction. From a technical point of view and under ideal conditions, this is supposed to be the absolute minimum for long-distance railway systems. Ideal conditions imply that connecting trains in “A” will stop on tracks that are closely to each other to shorten foot distances for passengers. It is also important that no large delay events may occur systematically for the connecting trains. The assumption of very high punctuality is made during the here presented model application. However, the authors of the paper entered into investigations regarding the reliability of very short transfer times within an IPT, which needs complex simulation of rail operations in heavily loaded networks.

For harmonization of train arrivals - which is mandatory for very short transfer times in node “A” - adjustments of travel times for trains approaching “A” are implemented within IPT 1 and IPT 2. It is important to notice that although the focus of investigations is on transfers in “A”, time symmetry and short transfer times of 6 minutes are assumed in the same way for the other nodes at the outer boundaries of the modeled network section. Thus, arbitrary shifting of departure times in nodes “B” to “I” is not a solution to avoid the need for travel time reductions. Instead, travel times between nodes must be at least exactly six minutes less than the full and half hour (e. g. 24 or 54 minutes).

The magnitudes of Non-IPT travel times between transfer-relevant nodes includes running times that are significantly too long (e. g. 70 min. instead of ca. 54 min.) as well as travel times that are only slightly missed (e. g. 59 min. instead of ca. 54 min.). For IPT 1 and IPT 2, assumed reductions of travel times starting from node “A” in direction “B” to “I” are in the order of –5 to –39 minutes (Table 7). These time savings which tend to be quite large are still within the bounds of what is planned on some relations after the introduction of the *Deutschlandtakt*. The potential for significant travel time savings for

Table 5
Basic assumptions for modeled railway lines.

Basic model assumptions in the “Non-IPT”-scenario	Railway lines				
	Blue	Violet	Red 1	Red 2	Green
seating capacity per train [-]	800	670	700	700	470
average seat occupancy rate per year [%]	69	67	70	65	55
ratio of work- / leisure- related journeys [%]	40 / 60	15 / 85	40 / 60	33 / 67	15 / 85
share of passengers with transfer in “A” [%]	29	50	23	26	73

Table 6
Changes in train frequency in the modeled railway network section.

Scope of modeled train frequency	Axes between transfer-relevant nodes within the network							
	A-B	A-C	A-D	A-E	A-F	A-G	A-H	A-I
train frequency Non-IPT [min]	120	60	30	60	60	60	60	60
train frequency IPT 1 [min]	60	60	30	30	60	60	60	30
train frequency IPT 2 [min]	60	60	15	30	60	30	30	30

Table 7

Average travel times respective travel speeds per traffic axis in the modeled railway network section.

Scope of modeled travel times and speeds	Axes between transfer-relevant nodes within the network							
	A-B	A-C	A-D	A-E	A-F	A-G	A-H	A-I
average travel time Non-IPT [h: min]	1:10	0:59	1:33	1:39	2:17	2:24	2:19	1:17
average travel time IPT 1 / 2 [h: min]	0:54	0:54	0:54	1:24	1:54	1:54	1:54	0:54
average travel speed Non-IPT [km/h]	115	125	115	155	100	135	145	140
average travel speed IPT 1 / 2 [h: min]	145	135	165	180	120	170	175	180

long-distance trains results from relatively low average travel speeds which do often not exceed 120 km/h. In some cases, newly constructed high-speed lines will significantly shorten travel distances and thus also save time. The objective in configuring the model network is to represent both smaller and larger increases in travel speed (Table 7). There is no slowing down of train traffic planned although in theory, this would also be a possibility to meet symmetry constraints. Travel times per source-target relation both for Non-IPT and IPT are provided in the appendix (Table 13 and Table 14).

In summary, differences between both timetable concepts Non-IPT and IPT 1 respectively IPT 2 can be summarized as follows: Travel time reductions result from reductions in transportation time (in-vehicle times) as well as from reductions of transfer times (waiting time at the station). Transportation time is reduced by approximately 39 minutes (−21.8%) on average. Transfer times in the central node of the network are reduced by 12 minutes (−54.2%) on average. The average reduction in travel time on both direct as well as non-direct connected source-target relations is 46 minutes (−23.9%) on average. A distribution of relative travel time reductions across all source-target relations is shown below in form of a box-plot-diagram. In terms of train frequency, in IPT 1, a halving of train intervals is modeled for about 40% of the source-target relations. In the IPT 2, the frequency is increased for about

60% of the source-target-relations (Fig. 3).

3.1.3. Definition of the network's tariff system

Apart from defining network's topology and its timetable, a tariff system is to be determined. When existing European tariff systems in Non-IPT railway networks with relatively low frequencies are considered, yield-optimized ticket pricing dominates. Its aim is to maximize seat occupancy while making the greatest possible use of passenger's willingness to pay. During peak hours and if tickets are bought shortly before departures, tickets are sold to maximum prices, skimming the willingness-to-pay of solvent and time-sensitive travelers, which to a larger extent include business travelers. By contrast, price-sensitive, mostly leisure travelers are steered to times of lower demand by very large price discounts. A common precondition for discounting is that tickets must be booked several weeks before the departure date. At this point, it is important to notice that temporal flexibility of starting a train journey is eliminated since discounts are forcing customers to a specific departure time and train connection. Taking the principles of yield optimization together, it fits best to relatively scarce seat availability during peak hours (regular prices charged) respectively – to a certain amount – unused capacities during off-peaks (price discounts). Since these framework conditions are also assumed for the modeled Non-IPT, a tariff system with strongly differentiated prices is elaborated.

From the authors' point of view, yield pricing is not the first choice for a railway network that has changed to an IPT respectively for a network with particularly dense train frequencies. One obvious point is that the greatly increased train offer mitigates limitations of seat capacity. Consequently, the objective can no longer be selling relative low seat capacity as expensive as possible but rather to manage increased seating capacities within attractive price levels throughout the day. Another, somewhat hidden aspect of an IPT system compared to Non-IPTs is increased planning uncertainty regarding passenger train loads. This has to do with the fact that even in the case of high punctuality levels throughout the year, a larger subset of total passenger demand is exposed to losses of connections at transfer-relevant nodes. Passengers then are obligated to switch to subsequent trains. Limited predictability of train loads stands in contrast with yield management which relies on accurate forecasts. Another aspect of yield pricing standing in conflict with an IPT is missing temporal flexibility for travelers. This contrasts with the basic idea of an IPT to create flexible travel options throughout the day without any planning effort. According to the authors, an IPT concept can only develop its full potential if no yield pricing is made, and fare structure is hold as simple as possible. This automatically results in reduced medium fares as high price-peaks should be eliminated.

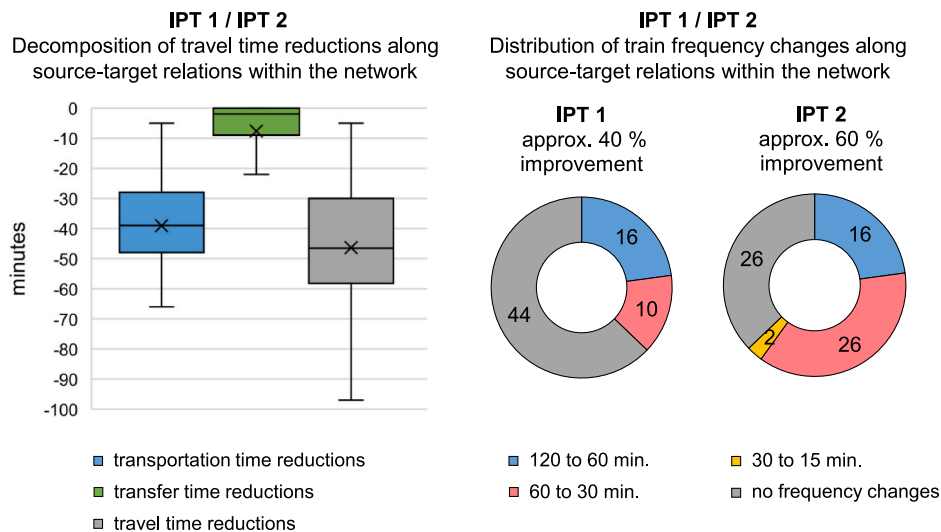


Fig. 3. Distribution of travel time reductions and train frequency changes in the modeled IPT railway network.

This is what we assume for the modeled IPT.

In both cases Non-IPT and IPT, ticket prices are calculated depending on four criteria, namely (1) travel times per source-target relation, (2) 1st or 2nd class tickets, (3) high-speed long distance-trains (ICE) or lower-speed long-distance trains (IC), and (4) 25% or 50% reductions due to annual subscriptions. The exact calculation of ticket-prices for each source-target-relation is based on assumptions, which are quite extensive. An illustration of the modeled ICE ticket price curves over travel times is given with the following figure (Fig. 4).

In the IPT case, a reduced regular price is set for the 1st and 2nd class and highly discounted yield prices are eliminated. By doing so, effects of a cheaper and less complex ticket price system are to be adopted as it would be conceivable in an IPT concept. The new regular price is derived by reducing the slope of the non-discounted price curves by approximately 50%. It should be noted that at least for some source-target-relations, the new pricing scheme results in higher fares for those passengers who had chosen discounted tickets previously. On the other hand, 25% or 50% discounts on regular prices are continued to be offered to passengers owning annual subscriptions. This will typically result in a price advantage as the reductions will now be applied to cheaper regular prices. Consequently, an increase of annual subscriptions allowing flat discounts on regular prices is assumed. Due to partially opposing price mechanisms, some customer groups and source-target-relations will be affected from little price increases. However, the customer's majority is profiting from price reductions up to 50% compared to the Non-IPT tariff system.

Economic viability of highly discounted long-distance passenger tariffs is currently investigated by the authors. Total cost / revenue calculations undertaken so far indicate that adequate measures are required to reduce fixed costs of rail to be profitable. However, this is not necessarily associated with an increase in tax-financed subsidies but – according to the authors' preliminary assessment – could also be achieved partly through economies of scale and system-wide efficiency improvements.

3.2. Description of the model algorithm

Key element of the model algorithm is the cumulative application of demand elasticities described in chapter 2.3. The model algorithm essentially contains the following input variables (Table 8).

The calculation is based on source-target relations ij within the modeled railway network section. For each source-target relation, percentual changes in travel time (Δt_{ij}), train frequency (Δf_{ij}) and ticket prices (Δp_{ij}) are multiplied with the corresponding elasticities to

Table 8

Variables used within the model algorithm.

D_{ij}	Rail passenger demand from source i to target j $D_{ij,0}$: Baseload $D_{ij,1}$: forecast scenario 1 $D_{ij,2}$: forecast scenario 2
D_l	Rail passenger demand per train line
a_m	Proportion of total passenger demand within one ticket price category, defined by ticket class, regular pricing or discounting, subscription to customer loyalty card
k	Trip purpose: $k = 1$: business; $k = 2$: leisure
n	Number of price categories used
p	Index for a scenario including ticket price changes (ceteris paribus)
r	Number of demand-relevant source-target-relations per train line
Δf	Change in train frequency
Δp	Change in ticket price
Δt	Change in travel time
ϵ_f	Elasticity value for train frequency
ϵ_p	Elasticity value for ticket price
ϵ_t	Elasticity value for travel time

obtain the relative changes in passenger demand. These changes are then summed up and multiplied by the baseload of the modeled network section. The procedure is given in equation form below, which is a simplified formula representation (Equation 5).

$$D_{ij,k,1} = D_{ij,k,0} \cdot \left[1 + \epsilon_{t,k} \cdot (\Delta t_{ij,1} / t_{ij,0}) + \epsilon_{f,k} \cdot (\Delta f_{ij,1} / f_{ij,0}) + \epsilon_{p,k} \cdot (\Delta p_{ij,1} / p_{ij,0}) \right]$$

Equation 5: Procedure for the cumulative application of elasticities used (simplified formula representation)

The calculation is in fact more comprehensive than the previous equation suggests. A major effort is that ticket price changes must be determined for all ticket price categories and weighted with ticket price elasticities according to trip purposes. In the case of the Non-IPT, ten ticket price categories were calculated both for business and leisure trip purposes and six ticket price categories in the case of the IPT 1 and IPT 2. To obtain the overall change in demand due to ticket price changes, calculations elaborated for individual ticket price segments are then summed up. This procedure is implemented by using shares of ticket segments (Equation 6).

$$D_{ij,k,p,1} = D_{ij,k,0} \cdot \sum_{m=1}^n a_m \cdot \left[1 + \epsilon_{p,k} \cdot (\Delta p_{ij,m,1} / p_{ij,m,0}) \right]$$

Equation 6: Specification of the procedure for the application of ticket price elasticities used

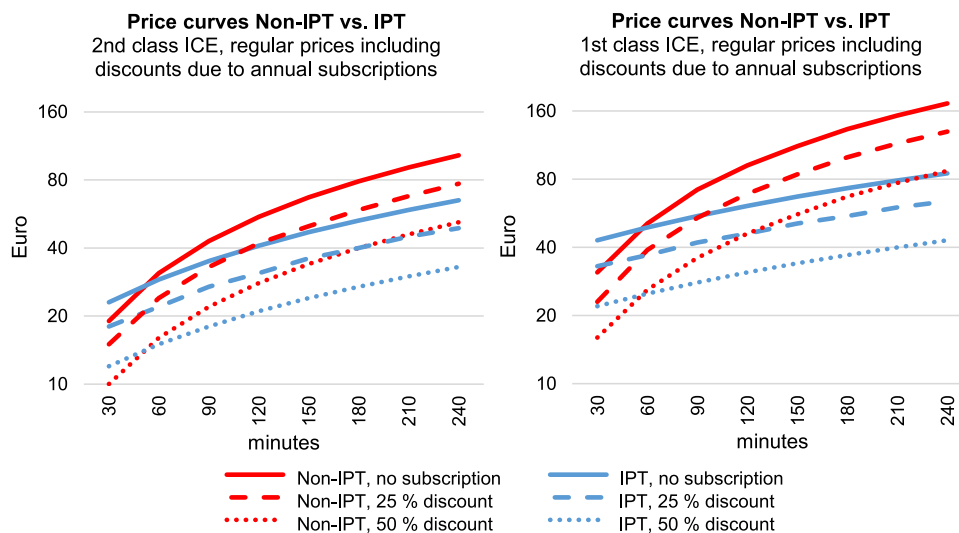


Fig. 4. Modeled ticket pricing depending on travel time, 1st and 2nd class for Non-IPT and IPT.

To obtain the rail passenger demand per train line, demand calculation is summed up over a set of source-target relations. These sets consist of direct connections as well as connections that require transfers (Equation 7).

$$D_l = \sum_{ij=1}^r D_{ij,k,l}$$

Equation 7: Aggregation of passenger demand volumes per train line

3.3. Results of the model application

Below, the results of four different model applications are shown in tabular form. Scenarios are split into the two IPT timetables (IPT 1 and IPT 2) combined with two different approaches for the application of demand elasticities (ϵ constant and ϵ variable). It is recalled that the distinguishing criterion between IPT 1 and IPT 2 is difference in train frequency (see chapter 3.1.2). Table 9 is representing results for “ ϵ constant”, which is seen as a conservative forecast. Table 10 is representing the results for “ ϵ variable” corresponding to a more optimistic approach, as described in chapter 2.3.

When all four scenarios are compared, rise of train-kilometers is between 27% (IPT 1) and 75% (IPT 2) accompanied by an increase in passengers transported between 24% (IPT 1, ϵ constant) and 42% (IPT 2, ϵ variable) compared to the Non-IPT. The rise in passenger-kilometers is 18% (IPT 1, ϵ constant) for a minimum, respectively 37% (IPT 2, ϵ variable) for a maximum compared to the Non-IPT. Travel time savings are in three of four scenarios the largest relative contributor to the increase in passengers as well as in passenger-kilometers (“travel time effect”). The application of larger elasticity values depending on distances (Table 10) almost doubles the travel time and cost effect compared to the application of conservative elasticity values before (Table 9). Train frequency has a huge impact on the average seat occupancy rates per train line within the modeled railway network section. In IPT 1, there are capacity bottlenecks in the number of seats offered since the occupancy rate runs up to 94% (Table 10). In IPT 2, the maximum average seat occupancy rate is 70% (Table 10). The considerable increase in train frequency expands available seating so that congestion can be avoided. On the other hand, model calculations show that minimum seat occupancy rates assumed for the “Non-IPT” (55%) are being undercut.

Table 9
Results of elasticity-based demand modeling using “ ϵ constant”.

modeled attributes	IPT 1 frequency increase for 40% of source-target relations	IPT 2 frequency increase for 60% of source-target relations
	ϵ constant	ϵ constant
Δ -train-km	+27.0%	+75.2%
Δ -passengers transported thereof	+23.5%	+30.5%
- „travel time effect“	+13.5%	+13.5%
- „frequency effect“	+ 7.3%	+14.4%
- „cost effect“	+ 2.6%	+ 2.6%
Δ -passenger-km thereof	+17.7%	+25.5%
- „travel time effect“	+ 9.0%	+ 9.0%
- „frequency effect“	+ 6.3%	+14.0%
- „cost effect“	+ 2.4%	+ 2.4%
ϕ seat occupancy rate ^a	43% - 85%	43% - 64%

^a mean values over the course of the day; span over the train runs within the railway network model

Table 10
Results of elasticity-based demand modeling using “ ϵ variable”.

modeled attributes	IPT 1 frequency increase for 40% of source-target relations	IPT 2 frequency increase for 60% of source-target relations
	ϵ variable	ϵ variable
Δ -train-km	+27.0%	+75.2%
Δ -passengers transported thereof	+34.8%	+41.9%
- „travel time effect“	+21.7%	+21.7%
- „frequency effect“	+ 7.3%	+14.4%
- „cost effect“	+ 5.8%	+ 5.8%
Δ -passenger-km thereof	+28.9%	+36.6%
- „travel time effect“	+17.2%	+17.2%
- „frequency effect“	+ 6.3%	+14.0%
- „cost effect“	+ 5.4%	+ 5.4%
ϕ seat occupancy rate ^a	44% - 94%	45% - 70%

^a mean values over the course of the day; span over the train runs within the railway network model

If productivity changes of the entire rail system changed to an IPT are evaluated, focus will be on comparison of growth rates for passengers transported / passenger-kilometers (output) and train-kilometers (input). Based on our example calculations, it can be stated as follows: If the implementation of an IPT is accompanied by considerable travel time or ticket price reductions but relatively few changes of train frequency, the growth rates for passengers as well as for passenger-kilometers tend to approach or even exceed that of train-kilometers. This is generally seen as productivity gain. In contrast, extensive increases in train frequency generate considerable additional demand effects, but these may still be too small to keep pace with the rate of increase in the train-kilometers (i.e. loss of productivity).

The results that were presented so far refer to the entire set of train runs within the railway network section. For more detailed interpretations, variations of demand effects along source-target relations are to be analyzed. In the following, variation spans of the travel time, frequency and cost effects on passenger demand along source-target relations are compared between the scenarios “IPT 1, ϵ constant” and “IPT 2, ϵ variable” (Fig. 9). It becomes clear that in the second scenario, the range of travel time and cost effects is significantly larger than in the first one. The mean value increases from +12.8% to +21.2% for the “travel time effect” and from +1.8% to +2.6% for the “cost effect”. The significant lower mean value for the “cost effect” compared to that of the “travel time effect” results from the fact that not only price reductions, but also slight price increases were assumed for some of the source-target relations. The mean value of the “frequency effect” increases from +7.5% to +11.6% due to increased train frequency affecting wider parts of the network.

Passenger growth is also evaluated per train line, which is shown exemplarily for scenario “IPT 1, ϵ constant” (Fig. 6) and scenario “IPT 2, ϵ variable” (Fig. 7). The impact of the travel time effect, the train frequency effect and the cost effect are added cumulatively. It can be seen for “IPT 1, ϵ constant” that demand growth of the blue line is influenced almost equally by the travel time and frequency effect. In case of the violet line, the frequency effect is dominant. Demand growth for the red lines and the green line is almost exclusively driven by the travel time effect. Application of higher elasticity values in “IPT 2, ϵ variable” causes the travel time effect to have the relatively most significant influence for all lines. Besides, train frequency effect gains importance as all lines except the green one have undergone a frequency change. The change in the ticket price system also has a stronger effect

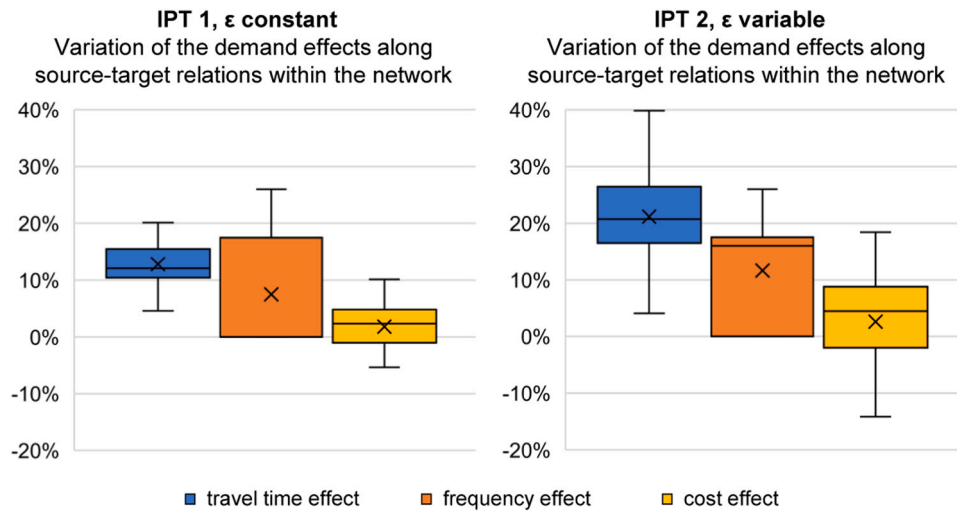


Fig. 5. Variation of demand effects along source-target relations within the railway network section.

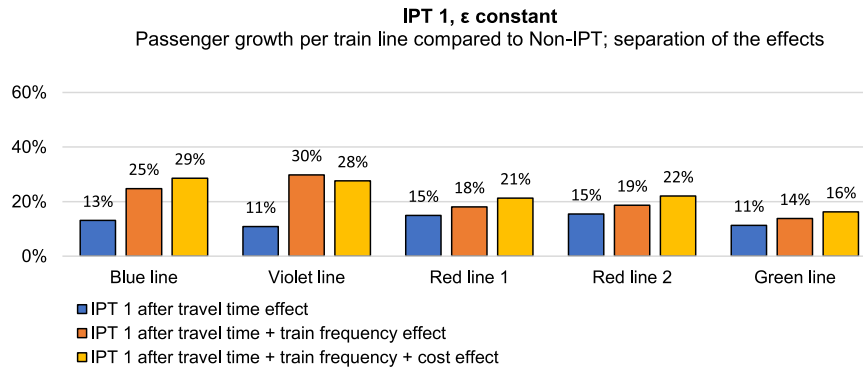


Fig. 6. Variation of passenger growth per train line, cumulative impact of demand effects - IPT 1, ϵ constant.

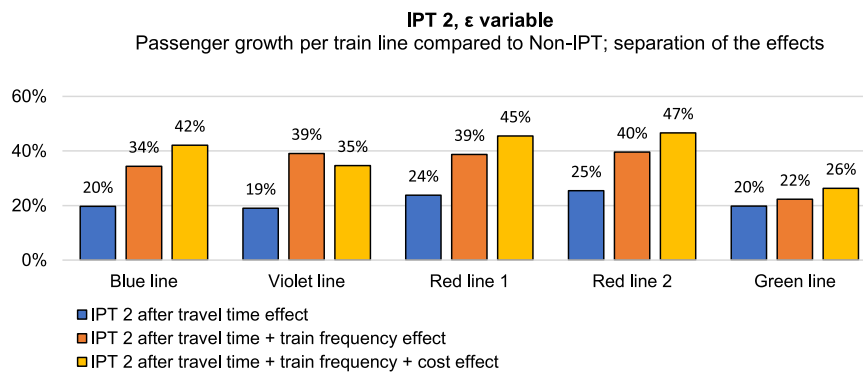


Fig. 7. Variation of passenger growth per train line, cumulative impact of demand effects - IPT 2, ϵ variable.

on demand due to higher elasticity values, except for the violet line. For this line, a significant acceleration of train speeds is assumed requiring higher-quality train material and thus leading to slightly more expensive ticket prices.

One interesting point is also differentiation of growth rates in total passenger demand between passengers with no need for transfers (direct traffic) and passengers with transfers in the central railway node “A” (transfer traffic). As it can be seen exemplary for the scenario “IPT 1, ϵ constant” below, passenger growth for transfer traffic exceeds growth of direct traffic in case of four out of five lines modeled (Fig. 8). This is mainly due to considerably larger travel time reductions for these

passengers profiting from shorter transfer times than for passengers using direct connections. For the blue line, a reverse trend is observable. This mainly relates to the fact that passengers using exclusively the blue line are profiting from an increase in train frequency whereas transfers to the red and green lines will continue to be offered at the former train frequency. The situation for the blue line changes in scenario “IPT 2, ϵ variable” (Fig. 9). Frequency increase is then also extended to the red lines. Growth for direct traffic of the violet line is shrinking in comparison to the previously discussed scenario due to already mentioned ticket price increases following acceleration and usage of higher-quality train material on this line. Transfer traffic using both violet and other

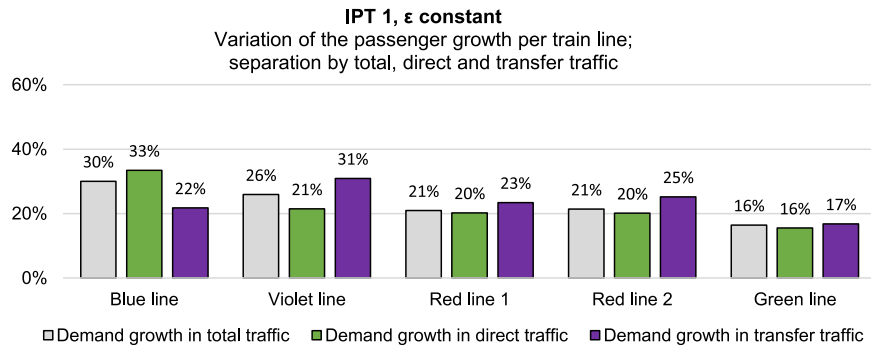


Fig. 8. Variation of passenger growth per train line, separated by direct and transfer traffic – IPT 1, ϵ constant.

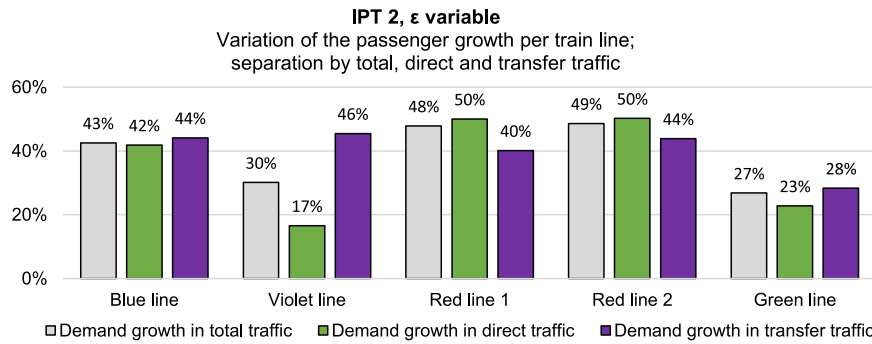


Fig. 9. Variation of passenger growth per train line, separated by direct and transfer traffic – IPT 2, ϵ variable.

lines is still profiting from constant or falling prices due to cheaper ticket prices at the other lines. The increase in passenger volume is more than doubled for the red lines compared to scenario “IPT 1, ϵ constant”. This has to do with doubled train frequency as well as with particularly huge travel time reductions resulting in stronger demand effects when variable elasticities for ticket prices are used. Regarding the green line, growth for transfer traffic is increased more significantly than for direct traffic. This mainly relates to high travel time reductions on particularly long-distance transfer connections, which are now contributing more to the demand effect through variable elasticity.

The question may now arise as to whether growth rates in total passenger demand could be achieved if only some of the IPT-typical features, but no ideal IPT would be implemented. Three control scenarios (CS) are elaborated. One basic control scenario is calculated without any transportation time reductions but increased train frequency and short transfer times (CS 0). Two further control scenarios imply non-optimized transfers in the central transfer node “A” but reduced transportation times (CS 1 and CS 2). In CS 1, train arrival times in “A” remain nearly the same as in Non-IPT. Transfer times are only shortened for very few source-target relations due to increased train frequency. In CS 2, trains leave nodes “B” to “I” at the same time as in Non-IPT but arrive in “A” significantly earlier due to reduced IPT travel times. This leads to transfers in node “A” which tend to be even less coordinated than in Non-IPT. The assumptions used for the control scenarios are summarized below (Table 11).

Transfer traffic growth rates for the control scenarios are shown below. Increase in transfer traffic for CS 0 is between +10% and +26% depending on the train line (Fig. 10). In CS 1, the increase is between +24% and +42% (Fig. 11). In CS 2, uncoordinated arrivals in “A” result in deviating growth rates for transfer traffic in the range of –4 to +1 percentage points compared to CS1 (Fig. 12). Short transfers are coincidentally produced for some of the transfer relations, notably for passengers using red line 1. Growth rates of CS 1 and CS 2 are –1 to –7 percentage points lower than those of “IPT 2, ϵ variable” (compare to Fig. 9). Reflecting this, it is to conclude that optimized transfers lead to

Table 11
Input parameters used for the calculation of control scenarios.

control scenario	transportation times	transfer times	train frequency	costs
CS 0	Non-IPT	IPT 1 / IPT 2	IPT 2	IPT 1 / IPT 2
CS 1	IPT 1 / IPT 2	approx. Non-IPT	IPT 2	IPT 1 / IPT 2
CS 2	IPT 1 / IPT 2	non-coordinated	IPT 2	IPT 1 / IPT 2

additional demand growth compared to a timetable concept based solely on reductions of transportation or transfer time. The exact growth rate depends, of course, on how much basic demand is on source-target relations requiring transfers (see basic model assumptions in Table 5).

It is now worth to notice that the demand effects that were discussed so far have also different implications for average seat occupancy rates per train run. This should be explained with reference to the following figures. Demand effects of travel time savings, increase in train frequency and ticket price changes are disaggregated by train line both for scenario “IPT 1, ϵ constant” as well as for scenario “IPT 2, ϵ variable”.

Beginning with “IPT 1, ϵ constant” (Fig. 13), it is particularly noticeable that the blue and the violet lines fall far behind seat occupancy rates of Non-IPT. This is because train frequency has been halved and even after cumulation of the three modeled demand effects, there is still a decline in average seat occupancy on these two lines. In the case of the violet line, average seat occupancy is further reduced due to modeled speed acceleration requiring ICE instead of IC trains which is resulting in a price increase (see also chapter 3.1.3). The situation is different in the case of the red lines and the green line where notably the travel time effect leads to significantly increased seat occupancy rates for these lines. At this point, it comes apparent that the red lines are serving the most accelerated source-target relations within the network which is resulting in the highest percentual travel time reductions. For

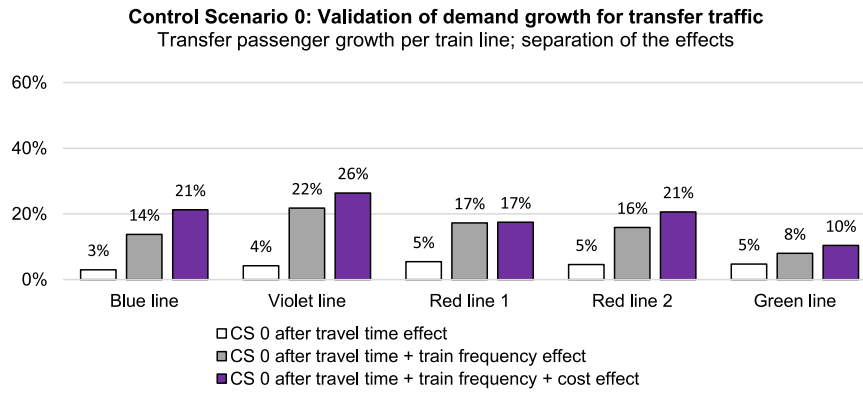


Fig. 10. Variation of passenger growth in transfer traffic for control scenario 0, ϵ variable.

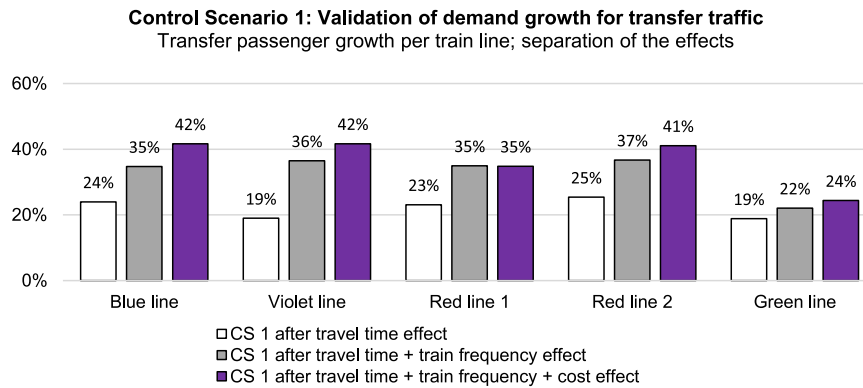


Fig. 11. Variation of passenger growth in transfer traffic for control scenario 1, ϵ variable.

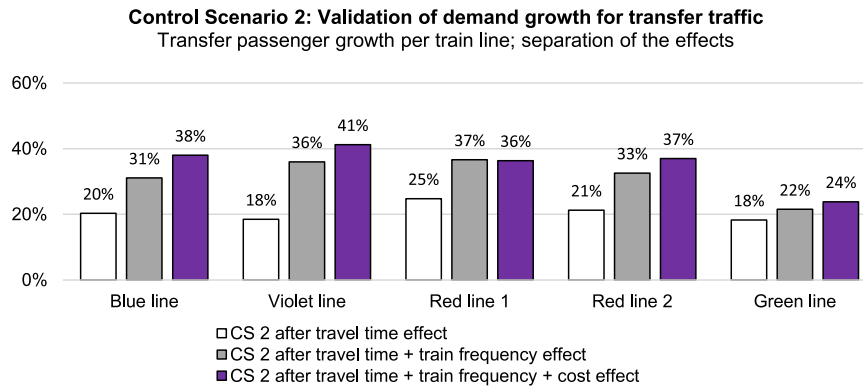


Fig. 12. Variation of passenger growth in transfer traffic for control scenario 2, ϵ variable.

the green line, a smaller increase in seat occupancy can be observed. This is notably due to relatively smaller gains in travel time.

Whilst regarding “IPT 2, ϵ variable” (Fig. 14), all train lines except the green line undergo a doubling of train frequency compared to the Non-IPT. This results in significantly lowered average seat occupancy rates per train run also for the red lines. Application of variable elasticity values for the variables “travel time” and “costs” and consideration of the “train frequency effect” cannot compensate at all for the fact that total demand is now spread over twice as many trains per day.

Finally, changed market position of long-distance rail passenger transport transferred from Non-IPT to IPT should be outlined by calculating generalized costs (GC) of rail compared to GC of road transport. As mentioned in chapter 3.1.1, demand calculations were made on a highly abstracted representation of a railway network section in northern Germany. In this region, the long-distance transport market is essentially

divided into rail transport and motorized private transport (direct flights and coaches only have marginal market shares). To compare the attractiveness of these two principal modes of transport, summation of gasoline / ticket costs and travel time costs was made for each source-target relation within the model network. Monetization of travel times was realized by using German values of travel time (VOT) according to means of transport, travel purpose and travel distance (Axhausen et al., 2014). Ratio of calculated GC of rail passenger transport compared to motorized private transport is shown below (Table 12). In the Non-IPT scenario, GC of business trips by train and private car are almost identical (ratio 0.93). In contrast, due to highly discounted train tickets used by train customers travelling for leisure, GC of leisure train trips are on average about 35% lower compared to GC of leisure car trips (ratio 0.65). In the IPT scenario, GC of business trips (ratio 0.65) as well as GC of leisure trips (ratio 0.51) decline sharply.

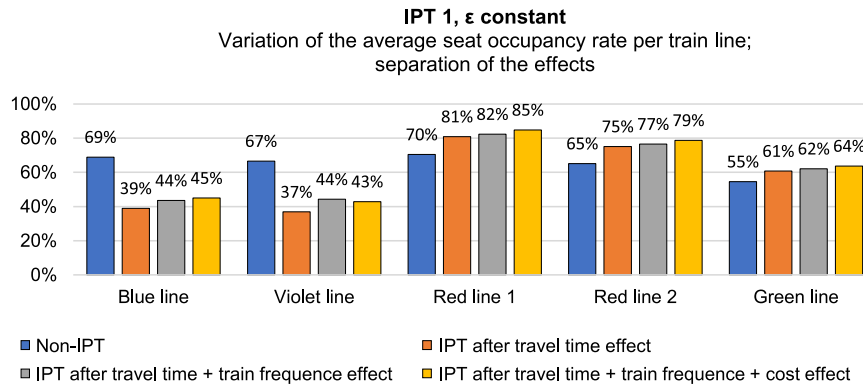


Fig. 13. Modeled variations of average seat occupancy rates per train line - IPT 1, ϵ constant.

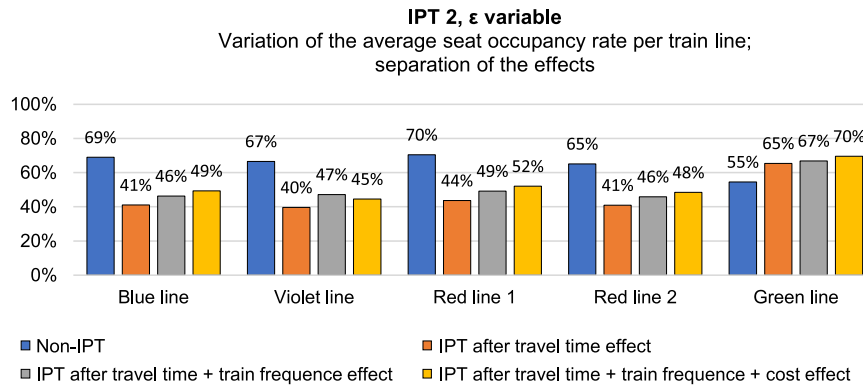


Fig. 14. Modeled variations of average seat occupancy rates per train line - IPT 2, ϵ variable.

Table 12

Comparison of the ratio of generalized costs (GC) between rail and motorized private transport for Non-IPT and IPT.

	Ratio "GC rail passenger transport" to "GC motorized private transport"			
	Non-IPT		IPT 1 / IPT 2	
	TP business	TP leisure	TP business	TP leisure
Mean (all modeled source-target relations)	0.93	0.65	0.65	0.51

Reflecting this, a significant modal shift from road to rail can be expected given that travel times and costs in motorized private transport remain constant.

4. Conclusions

Radical timetable innovations in long-distance railway passenger transport are gaining importance, as the German timetable concept *Deutschlandtakt* reveals. The political expectation of network-wide IPT introductions is to massively strengthen usage of passenger trains within very few years. However, the impact on overall demand remains uncertain. Current findings dealing with rail passenger demand cannot answer this question satisfactorily. This paper targets the question of how the introduction of an IPT could affect network-wide railway passenger demand. Decision was made to calculate demand reactions after introduction of an IPT illustratively by usage of demand elasticities. The focus is laid on elasticities of travel demand for the variables travel time, train frequency and costs as these features proved to be particularly relevant for travel mode decisions in railways.

To examine rail passenger demand after introduction of a network-wide IPT, a model environment as well as an elasticity-based algorithm for demand forecasting is developed. Within the model environment, a railway network topology, its baseload as well as different timetables and tariff systems are to be defined. According to the model environment, relative changes of travel times, train frequency and ticket prices are to be calculated and applied to the elasticity-based forecast of passenger demand. The model provides results both for the entire railway network section and for single rail lines. An exemplary model environment is carried out built on the idea of being able to represent conditions of the planned *Deutschlandtakt* as well as characteristics of an ideal typical IPT. Several prototypical research questions were processed through model application.

Our model calculations show that additional passenger demand depends on travel time savings very strongly. On the other hand, reduced gains in travel time greatly reduce the demand effect. With reference to the German IPT project *Deutschlandtakt*, leverage of significant potentials for travel time reductions is imaginable. Application of Swiss elasticity values depending on distances contribute to an almost doubled passenger growth compared to restrained German elasticity values. The model calculations also show positive implications of optimized transfer times on demand for transfer traffic. Control scenarios were elaborated to assess whether passenger growth rates calculated for an IPT could also be achieved if only some of the IPT-typical features would be implemented. By the analysis of time-related demand growth for transfer traffic, it was demonstrated that optimization of transfers leads to additional demand growth compared to a timetable concept based solely on reduction of transportation times. Another focus of the model application was laid on average seat occupancy rates. It became obvious that - notwithstanding significant overall increase in demand - doubling of train frequency can lead to greatly reduced seat occupancy rates. At this point, however, it must be stated that determination of train

vehicles in operation and thus number of available seats are business and / or political decisions. A profit maximizing strategy could even consider seat occupancy rates of above 90% to be desirable. Other strategies could deliberately plan for overcapacity in order being able to meet short-term peaks or additional demand above the anticipated level.

If productivity gains of the entire rail system changed to an IPT is regarded, it becomes clear that positive demand effects of an IPT might be assessed more critically in view of massively expanded train services. In our first IPT scenario, considerable travel time and ticket price reductions but relatively few changes in train frequency result in growth rates for passengers as well as for passenger-kilometers that tend to approach or even exceed that of train-kilometers. In contrast, in our second IPT scenario, massively increased train frequency contributes to the fact that demand growth cannot keep pace with the rate of increase in train-kilometers, which might be interpreted as productivity loss of the railway passenger system itself.

Our model algorithm was applied to one modeled railway network section representing conditions of the German *Deutschlandtakt* and characteristics of an ideal-typic IPT. For larger networks than the modeled one, the number of source-target relations will rise. Results of demand calculations would then be much more complex to interpret. However, referring to Germany's rail network topology, the authors still expect similar mechanisms of travel time reductions, increased train frequency and ticket price reductions on demand as it was modeled. This expectation is founded on heterogeneity of train lines and transfer requirements modeled that would also be observable on a nationwide scale. However, regarding other network topologies differing fundamentally from the German one, results must be viewed with caution. For example, if basic demand for transfers is very low and travel requests can be largely met by direct connections, an IPT will hardly have any benefits.

For our model applications, socio-economic and behavioral factors that might also contribute to demand effects were left unconsidered.

Appendix

Table 13 Average passenger demand assumed for Non-IPT (passengers per day and source-target relation)

	A	B	C	D	E	F	G	H	I
A	-	133	265	650	750	389	550	600	325
B	133	-	83	415	1305	578	390	415	154
C	265	83	-	166	1028	330	698	498	390
D	650	415	166	-	238	1163	3950	4500	1425
E	750	1305	1028	238	-	154	225	950	4500
F	389	578	330	1163	154	-	154	166	780
G	550	390	698	3950	225	154	-	-	900
H	600	415	498	4500	950	166	-	-	238
I	325	154	390	1425	4500	780	900	238	-

Table 14 Average travel times assumed for Non-IPT (h:min per source-target relation)

	A	B	C	D	E	F	G	H	I
A	-	1:10	0:59	1:33	1:39	2:17	2:24	2:19	1:17
B	1:10	-	2:09	2:43	2:52	3:27	3:34	3:29	2:27
C	0:59	2:09	-	2:32	2:38	3:38	3:23	3:18	2:16
D	1:33	2:43	2:32	-	3:12	3:50	4:00	3:55	2:50
E	1:39	2:52	2:38	3:12	-	3:56	4:03	3:58	2:59
F	2:17	3:27	3:38	3:50	3:56	-	4:41	4:36	3:34
G	2:24	3:34	3:23	4:00	4:03	4:41	-	-	3:41
H	2:19	3:29	3:18	3:55	3:58	4:36	-	-	3:36
I	1:17	2:27	2:16	2:50	2:59	3:34	3:41	3:36	-

Behavioral changes in terms of car ownership, for example, are still unexplored in the context of large-scale timetable innovations. Demand modeling could be further specified if demand elasticities exclusively for transfers in long-distance railway passenger transport would be available. Further need for research is also seen in specifying the pre-conditions for the high-quality operation of IPTs and related demand effects which is therefore subject of ongoing investigations by the authors. Further research should also cover the ex-post evaluation of the *Deutschlandtakt* to support and facilitate future demand forecasts.

Funding

Funded by the German Research Foundation (DFG) through individual research grant (project number 469042632).

CRediT authorship contribution statement

Bastian Kogel: Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Nils Nießen:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Fabian Stoll:** Writing – original draft, Visualization, Validation, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Univ.-Prof. Dr.-Ing. Nils Nießen reports financial support was provided by German Research Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 15 Average travel times assumed for IPT (h:min per source-target relation)

	A	B	C	D	E	F	G	H	I
A	-	0:54	0:54	0:54	1:24	1:54	1:54	1:54	0:54
B	0:54	-	1:48	1:48	2:24	2:48	2:48	2:48	1:48
C	0:54	1:48	-	1:48	2:18	2:54	2:48	2:48	1:48
D	0:54	1:48	1:48	-	2:18	2:48	2:54	2:54	1:48
E	1:24	2:24	2:18	2:18	-	3:18	3:18	3:18	2:24
F	1:54	2:48	2:54	2:48	3:18	-	3:48	3:48	2:48
G	1:54	2:48	2:48	2:54	3:18	3:48	-	-	2:48
H	1:54	2:48	2:48	2:54	3:18	3:48	-	-	2:48
I	0:54	1:48	1:48	1:48	2:24	2:48	2:48	2:48	-

References

- Avelino, F., Bömmelstroet, M., & Hulster, G. (2006): The Politics of Timetable Planning: Comparing the Dutch to the Swiss [Colloquium Vervoersplanologisch Speurwerk]. (<https://www.cvs-congres.nl/cvspdfdocs/cvs06.71.pdf>). Accessed 23.01.2023.
- Axhausen, K.W., Ehreke, I., Glemser, A., Hess, S., Jödden, C., Nagel, K., Sauer, A., Weis, C., 2014. Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf der Basis eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung: FE-Projekt 96.996/2011. TNS Infratest; IVT. ETH Zürich. (<https://doi.org/10.3929/ethz-b-000089615>).
- Behrens, C., Pels, E., 2012. Intermodal competition in the London-Paris passenger market: High-Speed Rail and air transport. *J. Urban Econ.* 71 (3), 278–288. <https://doi.org/10.1016/j.jue.2011.12.005>.
- Blainey, S., Hickford, A., Preston, J., 2012. Barriers to passenger rail use: a review of the evidence. *Transp. Rev.* 32 (6), 675–696. <https://doi.org/10.1080/01441647.2012.743489>.
- Cascetta, E., Coppola, P., 2015. New high-speed rail lines and market competition. *Transp. Res. Rec.: J. Transp. Res. Board* 2475 (1), 8–15. <https://doi.org/10.3141/2475-02>.
- CDU, CSU, SPD (Ed.) (2013). Deutschlands Zukunft gestalten: Koalitionsvertrag zwischen CDU, CSU und SPD. 18. Legislaturperiode. (<https://archiv.cdu.de/sites/default/files/media/dokumente/koalitionsvertrag.pdf>).
- Garcia-Martinez, A., Cascajo, R., Jara-Diaz, S.R., Chowdhury, S., Monzon, A., 2018. Transfer penalties in multimodal public transport networks. *Transp. Res. Part a: Policy Pract.* 114, 52–66. <https://doi.org/10.1016/j.tra.2018.01.016>.
- Gundelfinger-Casar, J., Coto-Millán, P., 2017. Intermodal competition between high-speed rail and air transport in Spain. *Uti. Policy* 47, 12–17. <https://doi.org/10.1016/j.jup.2017.06.001>.
- Iseki, H., Taylor, B.D., 2009. Not all transfers are created equal: towards a framework relating transfer connectivity to travel behaviour. *Transp. Rev.* 29 (6), 777–800. <https://doi.org/10.1080/01441640902811304>.
- ITS, Leigh I.Fisher, & Rand Europe (2016): Rail Demand Forecasting Estimation: Final Report. (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/610059/phase2-rail-demand-forecasting-estimation-study.pdf). Accessed 23.01.2023.
- Nordenholz, F., Winkler, C., & Knörr, W. (2016): Verkehrsverlagerungspotenzial auf den Schienenpersonenfernverkehr in Deutschland unter Beachtung infrastruktureller Restriktionen: Endbericht im Rahmen der Wissenschaftlichen Begleitung, Unterstützung und Beratung des BMVI in den Bereichen Verkehr und Mobilität mit besonderem Fokus auf Kraftstoffen und Antriebstechnologien sowie Energie und Klima [AZ Z14/SeV/288.3/1179/UI40]. (https://bmdv.bund.de/SharedDocs/DE/Anlage/G/MKS-Wissenschaftliche-Untersuchungen/studie-verlagerungspotenzial-schienenverkehr-restriktionen.pdf?__blob=publicationFile). Accessed 23.01.2023.
- Sievering, O., 2021. Elastizitäten. In: Drewello, H., Kupferschmidt, F., Sievering, O. (Eds.), *Markt und Staat*. Springer Fachmedien Wiesbaden, pp. 69–81. https://doi.org/10.1007/978-3-658-33096-5_3.
- SMA and Partner (2021): Fahrplan Schweiz 2022: Gültig ab 12. Dezember 2021 bis 10. Dezember 2022. (https://sma-partner.com/storage/app/media/Dokumente/Netzgrafiken/Netzgrafiken-Fahrplan-Schweiz-2022_de.pdf). Accessed 23.01.2023.
- Wardman, M., 2022b. Meta-analysis of price elasticities of travel demand in great britain: Update and extension. *Transp. Res. Part a: Policy Pract.* 158, 1–18. <https://doi.org/10.1016/j.tra.2022.01.020>.
- Wardman, M., 2022a. Meta-analysis of British time-related demand elasticity evidence: an update. *Transp. Res. Part a: Policy Pract.* 157, 198–214. <https://doi.org/10.1016/j.tra.2022.02.001>.
- Weis, C., Vrtic, M., Schmid, B., & Axhausen, K.W. (2017): Analyse der SP-Befragung 2015 zur Verkehrsmodus- und Routenwahl. (https://www.are.admin.ch/dam/are/de/dokumente/verkehr/dokumente/bericht/analyse_stated_preference_befragung_2015.pdf.download.pdf/Analyse_Stated_Preference_Befragung_2015.pdf). Accessed 23.01.2023.
- Williams, I., & Jahanshahi, K. (2018): Wider Factors affecting the long-term growth in Rail Travel (Report). (<https://www.theitc.org.uk/wp-content/uploads/2017/05/ITC-Report-Rail-Passenger-Demand-November-2018.pdf>). Accessed 23.01.2023.