Flightpath 2050 door-to-door travel time goal: 
A comparative study on Europe and China

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Abstract—SESAR Flightpath 2050 sets several ambitious goals for European transportation in the year 2050. One of these goals concerns door-to-door travel time, which aims at having “90% of travellers complete their journey, door-to-door within four hours”. This goal, however, is missing a clear baseline, i.e., “How good is the current door-to-door accessibility?”. In order to find answers to this question, this study develops a model to assess the door-to-door accessibility for Europe and China at a high resolution. Urban center data is integrated into a radiation model for passenger travel flow estimation; a multi-modal door-to-door travel framework is established, combining rail with air transportation, to estimate door-to-door travel times. Accessibility indicators are proposed to measure the satisfaction of travel demand for each urban center and the complete region/country. Results show that transport infrastructure at the current stage has already the potential to meet the ambitious four-hour goal in both regions. Contrary to intuition, large urban areas have a more urgent need to improve accessibility with respect to the given goal, induced by their large travel demand, compared to smaller urban areas.

Keywords: Door-to-door travel; Accessibility; Flightpath 2050

I. INTRODUCTION

SESAR Flightpath 2050 [1] lays out several long-term goals for Europe by 2050. One of the ambitious goal claims that “90 percent of travelers within Europe are able to complete their journey, door-to-door within four hours”. For China, “Mid- and Long-Term Railway Network Plan” [2] aims at achieving an one to four hours traffic circle between neighboring large- and medium-sized cities. Some studies have suggested that one-way trips with more than four hours make it difficult for people to travel comfortably within a day [3]. The preferable travel time is generally three to four hours, because it is possible to return to the starting point in one day and perform corresponding activities at the destination [4]. All these show that the four-hour travel time is a key threshold. Conventional approaches to estimate travel time include GIS systems [5], [6] and mapping services like Google or Bing Maps [7], [8]. Cell phone location data is used to infer users’ home and work place, and further to estimate travel times [9], [10], [11]. GIS systems need a large amount of fundamental geographical data; mapping queries are usually restricted by commercial APIs; while cell phone data involves privacy issues and often only cover a small area. Open source dataset provided by OpenStreetMap [12] captures detailed and precise transportation infrastructure information, and has been used for efficient minimum travel time estimation at regional or planet scale [13], [14], [15]. Travel time is a commonly used and interpretable indicator for measuring the ease of access, which is the so-called accessibility [16]. The accessibility of urban centers, railway stations, and airports has been extensively studied [15], [17], [18], [19].

The purpose of this research is to design and implement a model to measure door-to-door travel times and assess the level of accomplishment of the four-hour goal. We focus on door-to-door travels for medium and long distance, taking into account three different transportation modes: car, air, and railway. Based on these three transportation modes, a door-to-door multi-modal travel framework is built to estimate travel times between every two urban areas. We use the radiation model for travel demand estimation. Combining the travel time results and travel demand results, we propose two indicators to measure accessibility for each city and the overall accessibility for a region or country. Compared with existing research, major contributions of this study are summarized as follows: 1) Different from [20], [21], which just provided case studies for a few city pairs, this study considered all urban areas over Europe and China. 2) This study provide more accurate estimation for travel times based on real timetables of trains and flights, compared to lower bounds in [14]. 3) This study considers a multi-modal travel pattern combining air and rail, instead of considering transport modes separately like [14], [20]. 4) Finally, this study explicitly tries to identify a reference baseline for the goal identified by Flightpath 2050.

The rest of the paper is organized as follows: Section II introduces the our multi-modal travel model, the travel demand estimation methodology, and our definition of accessibility. Section III describes the study area and corresponding datasets. The results are presented in Section IV. Section V concludes this study and discusses future research directions.

II. MODEL AND METHOD

A. Multi-modal door-to-door travel model

Multi-modal travel refers to a journey consists of a combination of transport modes, and the journey may involve transfer within or across modes. In this study, we focus on medium and long distance journey, considering the combination of three transport modes – air, rail and driving – to simulate the seamless door-to-door travel. For the sake of readability, we refer to airports and railway stations as terminals, trains and flights as scheduled service (also just service). In multi-modal door-to-door travel, each journey is constructed as a sequence of journey-legs, of which in general the first and last legs — connecting the origin and destination to terminals—involve driving, and the middle legs involve scheduled services between terminals. Besides, there may be transfers between different terminals. Initially, there is no limit on the number of
middle legs in a journey, and the combination possibilities can be extended (e.g., Car → Rail → Rail → Car, Car → Rail → Rail → Air → Car,...). Based on the travelers’ preference, we set the maximum number of middle legs as three, which means at most two transfers are permitted during a journey. Transfer can occur at the same terminal (which is noted as intra-transfer), and can occur between different terminals (which is noted as inter-transfer). Furthermore, for a journey from origin O to destination D, the travel duration consists of a series of en-route times (the time actually spent in vehicles) and non-zero buffer intervals. These buffer intervals may involve: (a) necessary time spent at the departure terminal (e.g. check-in, security check, boarding) and the arrival terminal (e.g. security check, baggage delivery); (b) the time spent waiting for the scheduled services; and (c) time needed to transfer to other terminal (if it is inter-transfer). The travel duration T_{OD} is formulated as:

\[ t_{OD} = t_{access} + \sum_{i=1}^{n} \left( t_{buffer}^{i} + t_{scheduled}^{i} \right) + t_{buffer}^{i+1} + t_{access}, n = 1, 2, 3 \]

where \( t_{access} \) is the time needed by car from origin O to the first departure terminal; \( t_{access} \) is the time needed driving from the last arrival terminal to the destination D; \( t_{buffer} \) and \( t_{scheduled} \) is buffer time and en-route (air, train) time described above. Obviously, the travel is a direct journey with \( n = 1 \), and involves transfer with \( n = 2, 3 \). For the same origin-destination pair OD, different journey-planning process leads to different travel duration T_{OD}:

1) Different starting time of the journey. Start time of the journey affects whether one can catch up a scheduled service or not, and the time spent waiting to depart.
2) Different (combinations of) transport modes. Both air and train are optional, and transfer offers more options.
3) Different routes. There may be more than one terminals near the origin point and the destination point. Travellers can choose different terminals to start/end their journey.

In this study, we estimate the shortest travel duration with respect to different starting time, while routes and (combinations of) transport modes are automatically selected by the minimum travel duration rule. There are three steps: Creating a multi-modal service network; setting up a lookup table for departure terminal, departure time, arrival terminal, arrival time; Computing shortest travel duration between origin and destination with certain starting time.

B. Travel demand estimation
In this study, travel demand is estimated by radiation model [22]. The flow from zone i to zone j is computed as:

\[ T_{ij} = T_{i} \frac{m_{i}m_{j}}{(m_{i} + s_{ij})(m_{i} + m_{j} + s_{ij})} \]

where \( m_{i}, m_{j} \) are the population in zone i and zone j, respectively; \( s_{ij} \) is the total population in zones within a circle of radius \( d_{ij} \) centered at i while excluding population in zone i and zone j; \( T_{i} \) is the total number of travellers that start their journey from zone i.

In the radiation model, flows are modeled in a parameter-free way, which take only the population distribution as input. The model overcame limitations of classical gravity model [23], which depends on historical empirical data to calibrate model parameters. In this study, we utilize radiation model to estimate passenger flow (i.e., travel demand) between urban areas in the absence of empirical trip data. We use the urban areas data defined based on population size and built-up area densities (see Section III), instead of administrative units as defined by individual countries. The use of consistent data and methodology makes our results comparable. Note that the analysis of radiation model [22] was made over US counties. Much work has been done to access the universality and accuracy at different spatial scales, using different datasets [24], [25], [26]. Spatial scale and the population heterogeneity limit the predictability of radiation model. The distribution for the population of urban areas follows Zipf’s law (see results in Section III), which indicates population heterogeneity of the system. A normalized version [25] was proposed to take into account heterogeneity. The model fixed underestimation of the flows of the original model by a factor \( \frac{1}{i} \). It can be seen from the normalization factor that the underestimated for big urban and small urban (with small population) is different. In order to get a better estimation for travel demand fitting for urban data, we use the normalized radiation model for this study.

C. Accessibility measurements
Accessibility has various definitions and one of the well-known and generally accepted ones is "the potential of opportunities for interaction" [27]. "Relative accessibility" is proposed and defined as "the degree to which two places or points on the same surface are connected" [28]. As mentioned above, the measurement indicators can be different depending on the research goal. In this study, we aim to estimate the time required to travel to different locations by means of (combinations of) transport modes. We follow the essential idea of relative accessibility, and define the accessibility in this study as to what extent travel demands are met. The accessibility is a fraction with a maximum value of 1.0, whose denominator is the satisfied travel demand, and numerator is the total travel demand. Higher value indicates better satisfaction of travel demand. There are two types of accessibility in this study:

1) Accessibility of an urban center i within a travel time threshold \( t_{d} \):

\[ A_{i}(t_{d}) = \frac{\sum_{k \in \{k|t_{ik} \leq t_{d}, k \neq i\}} T_{ik}}{\sum_{j \neq i} T_{ij}} \]

where \( T_{ik} \) is the travel demand from i to k; k is urban center in the set of urban areas where the travel time \( t_{ik} \) is no more than \( t_{d} \); j is an urban center in the set of the whole urban areas.

2) Overall accessibility within a travel time threshold \( t_{d} \)

\[ OA_{i}(t_{d}) = \frac{\sum_{i} \sum_{k \in \{k|t_{ik} \leq t_{d}, k \neq i\}} T_{ik}}{\sum_{i} \sum_{j \neq i} T_{ij}} \]

Here \( A_{i} \) measures the accessibility of each urban center i; while \( OA_{i} \) is the satisfied travel demand of the
region/country over total travel demand. For example, $A_{Paris}(4h)$ measures the fraction of satisfied travel demand of Paris (urban center) within four hours’ travel to total travel demand. $OA^{China}_{China}(4h)$ measures the satisfied travel demand of China over total travel demand of this country.

III. STUDY AREA AND DATA

A. Study Area

In this study, two large scale regions are considered — one is 17 neighboring European countries, the other is Mainland China including Hainan island. The total land area of these 17 countries located at central Europe, with about 3.53 million square kilometer; the total population is 433 million. Mainland China covers an area of 9.38 million square kilometers, and have a total population of 1.39 billion. This information is statistically derived from GPWv4 (Gridded Population of the Word) data. We focus on intercity transport system. In order to ensure the consistency of methodology and data for both Europe and China, we extract urban centers from GHS Settlement Model grid (GHS-SMOD) dataset, instead of using administrative units as defined by individual countries. GHS Settlement Model grid (GHS-SMOD)[29] is a dataset which classifies settlement typologies based on a logic of population size and built-up area densities to measure the degree of urbanization. We selected the urban centers’ variant (also ”High Density Clusters”(HDC)) of the dataset, which is defined as ”contiguous grid cells with a density of at least 1,500 inhabitants per square km or a density of built-up surface greater than 0.5, and has at least 50,000 inhabitants”. We extracted 605 unique urban centers for Europe, and 1,834 urban centers for Mainland China. European urban population accounts for 38.94% of the total population. China urban population accounts for 40.26% of the total population. An overview of urban centers together with population, stations and airports is provided in Table I.

Figure 1 shows the locations of urban centers in Europe, and China. Following normalized radiation model (Equation 3), we computed the travel demand for every urban pair. Top 1000 travel demand is also shown in Figure 1. Compared to Europe,
TABLE I: Overview of the 17 European countries and China in this study, including the ISO3 code, population, the number of urban centers (HDCs), the population of HDCs, the number of stations, and the number of airports for each country.

<table>
<thead>
<tr>
<th>ID</th>
<th>ISO3</th>
<th>Name</th>
<th>Population</th>
<th>HDCs</th>
<th>Population of HDCs</th>
<th>Stations</th>
<th>Airports</th>
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<td>1</td>
<td>AUT</td>
<td>Austria</td>
<td>8,643,446</td>
<td>6</td>
<td>2,637,767</td>
<td>181</td>
<td>6</td>
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<td>3,633,563</td>
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<td>2,906,893</td>
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<td>Czech Republic</td>
<td>10,423,377</td>
<td>12</td>
<td>2,323,924</td>
<td>146</td>
<td>3</td>
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<td>26,371,687</td>
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<tr>
<td>6</td>
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<td>Denmark</td>
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<td>1,655,168</td>
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<td>62</td>
<td>20,149,737</td>
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<td>6</td>
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<tr>
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<td>20,925,349</td>
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<td>10,613,523</td>
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<tr>
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<td>28</td>
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<tr>
<td>18</td>
<td>CHN</td>
<td>China</td>
<td>1,387,832,072</td>
<td>1,834</td>
<td>558,806,629</td>
<td>2,189</td>
<td>228</td>
</tr>
</tbody>
</table>

the distribution of urban centers is denser and uneven in China. Clearly, big urban centers emit high travel demand to surrounding locations. Typical representatives are London, Paris, Madrid, Barcelona, Berlin, Milan for Europe, and Beijing, Shanghai, Guangzhou, Wuhan, Chengdu for China. It’s worth noting that these big urban centers are usually connected, which means that they are both radiation sources (i.e. journey origins) for large travel needs, and absorbers (i.e. destinations of journey) of large travel needs.

Figure 2 shows the cumulative frequency distribution for the population of urban areas. Clearly the urban size distribution follows Zipf’s law [30], i.e., 

\[ P(p > p^*) = \frac{C}{p^\alpha}, \]

for Europe \( C = 5.6, \alpha = 1.2 \) and for China \( C = 5.5, \alpha = 1.2 \).

B. Data

After clarifying the features of areas under study, we introduce the data sources collected for our multi-modal travel model. As explained above, there are three modes driving, train, air involved. Driving time is estimated by a routing engine OSRM. Timetable datasets are collected since train and air are scheduled services. Details are as follows:

1) **OpenStreetMap (OSM):** OpenStreetMap\(^1\) (OSM) is a collaborative project that aims to create a free editable map of the world, started in 2004. OSM relies on volunteers to contribute data and the data is free to be downloaded, used, and redistributed. Through continuous improvement, OSM has become one of the most accurate and complete infrastructure datasets in the world [12]. A variety of transportation related infrastructures are properly modeled, such as physical layout of streets, free ways, rails, speed limits, railway stations, airports, etc. In this study, location data for railway stations in Europe and China are extracted from OSM data. OSM data is used to estimate the driving time between any two points inside Europe or China.

2) **Open Source Routing Machine (OSRM):** Open Source Routing Machine\(^2\) (OSRM) is a routing engine for calculating routes, distances, and travel times between spatial locations. It is an open-source project used on top of OSM data. Based on contraction hierarchies [31] or multilevel Dijkstra’s algorithm [18], OSRM provides very fast query speed to compute the shortest path (usually below 1 millisecond for data sets like Europe). Road-specific speed-limit information, turn restrictions, and turn lanes are taken into consideration by OSRM, which makes the free-flow travel time estimation very accurate. A local OSRM instance was built for Europe and China, in order to avoid query restrictions on official server. The API is convenient by specifying the coordinates of origins and destinations. The results of a query include segmented routes, corresponding driving distance and time taken. In this study, we use OSRM to simulate road transportation, for routing door-to-terminal, inter-terminal transfer, and terminal-to-door, to estimate the duration of each segment.

3) **Schedule Data:** The schedule datasets are collected from multiple data sources. For China, the schedule data for 7,498 passenger railway trains was obtained from the official website\(^3\) of the Railway Customer Service Center of China on 27 November, 2019. Data fields include train number, stations together with departure, arrival times at each station. Schedule data for 11,803

\(^1\)http://www.openstreetmap.org

\(^2\)http://project-osrm.org

\(^3\)http://12306.cn
A. Experiment settings

In order to make the multi-modal door-to-door travel model realistic, there are some parameters and constraints. First of all, travellers start their journey at an origin point, they need to access an origin terminal (station or airport) by means of driving. Most railway stations are located in urban areas, and more dense than airports, while airports are often far from urban and take longer to access. Based on this situation, we limit the selection of railway stations to within an hour’s driving, while allow the searching for airports within two hours’ driving. We didn’t further limit the number of candidate airports or stations in the time radius, that means one may have multiple airports or stations to select to start their journey. For example, for travellers in Beijing, main candidate railway stations include Beijing, Beijing West and Beijing South; and two candidate airports are Beijing Capital International Airport (PEK) and Beijing Daxing International Airport (PKX). Secondly, passengers need to spend the necessary processing time. The accessibilities analysis generates 605 results for Europe and 1,834 results for China. Figure 3 reports the accessibilities of urban areas for Europe (a) and China (b). The blue curve (together with error band) shows the result for all urban areas. We selected a subset of urban areas – top 50 urban areas, which is shown in orange curve (together with error band). For Europe, 573 urban areas reaches 90% accessibility within 4 hours’ multi-modal travel. For China, 1,774 urban areas reaches 90% accessibility within 4 hours’ multi-modal travel. From this perspective, the accessibility results for urban areas are optimistic, but the top 50 urban areas have lower accessibility.

To help explain the results of Figure 3, we analyze the distribution of the travel demand with distance for top 50 urban areas and the remaining urban areas. The visualization is shown in Figure 4. Following Zipf’s law for urban size distribution, the top 50 urban areas account for half of the country’s (region’s) travel demand (for Europe, the ratio is 54.0%; for China, the ratio is 45.1%). In other words, the top 50 urban areas split travel demand nearly equally within the rest, which is why the two curves have the same order of magnitude and can be drawn and compared with a single figure. We show that the travel demand distribution of top 50 urban areas have different patterns from the rest areas— has relatively large demand in long distances. This phenomenon has been intuitively shown in Figure 1, in which top 1000 travel demand consists lots of long distance links from/to large urban areas. Apparently, longer distance induce longer travel duration, which is the reason why the travel demand of top 50 urban areas becomes “harder” to satisfy.

With the same settings as above, we computed the overall accessibility in best case. As discussed before, overall accessibility is an aggregation for a region/country. Figure 5 shows the accessibilities with respect to travel time under three cases. From these curves, it is intuitive to see the satisfaction of the travel needs. With multi-modal travel, 90% travellers are able to complete their door-to-door journey within 3.8 hours within Europe. China shows the similar overall accessibility as Europe – four hours are sufficient to satisfy 90% travel demand.

First, we consider the accessibility in best case for each urban center. The best case assumes that travellers plan their starting time according to the envisaged scheduled departure time ensuring to spend no waiting time at the terminal except for the necessary processing time. The accessibilities analysis generates 605 results for Europe and 1,834 results for China. Figure 3 reports the accessibilities of urban areas for Europe (a) and China (b). The blue curve (together with error band) shows the result for all urban areas. We selected a subset of urban areas – top 50 urban areas, which is shown in orange curve (together with error band). For Europe, 573 urban areas reaches 90% accessibility within 4 hours’ multi-modal travel. For China, 1,774 urban areas reaches 90% accessibility within 4 hours’ multi-modal travel. From this perspective, the accessibility results for urban areas are optimistic, but the top 50 urban areas have lower accessibility.

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We analyze further how travellers select their start times of journey, in order to obtain shortest travel duration (i.e., the “best case”). For each origin-destination pair, we compute the shortest travel duration and record the start time of the journey. In this way, we got 605 x 604 records for Europe, and 1834 x 1833 records for China. We group these start times every one hour period (e.g., 0:00-01:00, 1:00-02:00, ..., 23:00-00:00). Results are visualized in Figure 6. Firstly, it is consistent with common sense that late night and early morning (i.e., later than 8:00 PM and earlier than 4:00 AM) are not good options to start a journey. Few OD pairs get the best connectivity (i.e., shortest travel duration) at these time periods, for both Europe and China. In contrast, 7:00 – 9:00 AM is a peak, which correspond to morning peaks of travel. To some extent,
Fig. 3: Accessibility in best case of Europe and China. Curves show accessibilities aggregated in 0.1-hour increments, showing confidence bands with standard deviation.

Fig. 4: Correlations of the travel demands with distance. All the plots are in log-log scale, which reveals power-law shape.

Fig. 5: Overall accessibility of Europe and China. Curves show overall accessibilities aggregated in 0.1-hour increments.

Figure 6 explains the rationality of flight and train scheduling at this stage — ensuring short-duration and efficient travel during peak hours. It also can be seen from Figure 6 that the distribution of Europe (a) and the distribution of China (b) is different. The distribution of China is steep, and only has one peak at around 8:00 AM. While the distribution of Europe is smoother and has another small peak at around 14:00 PM. The second peak of Europe may be related to the distribution of departure times of trains and flights, see Figure 7.
To evaluate where Europe stands regarding SESAR Flightpath 2050 four-hour travel goal, this study created a door-to-door travel model, collected multiple datasets and defined accessibility indicators. In addition we compare the results to another continental-size regions: China. Results show that transportation infrastructure at the current stage can meet this ambitious four-hour goal in best case. While compared to small urban centers, large urban centers have a more urgent need to improve accessibility due to their large travel demand. In order to make this study feasible, we had to make a few assumptions; limitations which could be addressed in future work:

1) Congestion and delays are important factors for travel
time, especially during rush hours. For our transfer model, we assume free-flow times. Delays can lead to the unavailability of subsequent services.

2) We do not consider capacities in our model, assuming that all passengers can realize their user-optimal travel choice.

3) This study only aims at the shortest travel time, while when further consider the preferences and economic constraints of different passenger groups, the results may be different. Future work could aim at considering other factors such as travel fares.

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