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Multiple airport regions based on inter-airport temporal distances

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ABSTRACT

We formulate and implement a new metric for identifying multiple airport regions (MARs) around the world, based on the temporal distance between airports. This metric, opposed to existing studies based on spatial distance, takes into account the real travel time between airports of latent passengers and their journeys via ground transportation. We investigate a variety of properties of the newly built MARs network at the global scale for the year 2015, including the importance of MARs in global air transportation, similarity clustering, destination overlap, and airport roles inside a MAR. Commonalities and differences to the simplified spatial distance are identified.

1. Introduction

Global air transportation faces tremendous demands and challenges (Balakrishnan et al., 2016; Cook et al., 2015; Wandelt and Sun, 2015). Meeting these high demands is critical, since current air transportation already suffers from significant congestion and delays (Belkoura et al., 2016), as well as hard criticisms on its negative environmental impacts (Wolfe et al., 2014), especially noise and emission in the vicinity of airports (Forsyth, 2007). Capacity at many airports is limited relative to current or projected passenger demands (Fernandes and Pacheco, 2002). Recent studies have increasingly used complex network techniques (Cook et al., 2015) to understand the processes of delay generation (Belkoura et al., 2016), delay propagation (Zanin, 2015), loss-of-separation (Zanin, 2014), and resilience (Sun et al., 2017). In such studies, analyzing the roles and functions of a single airport often provides a limited view on the real geography of air transport in general, especially in metropolitan areas where more than one airport serve the passengers with increasing long-distance mobility demand in a region (O'Connor and Fuellhart, 2016). Therefore, it is believed that the concept of Multiple Airport Regions (MARs) is an effective starting point for air transport research. The concept of MARs has emerged in the 1990s: It was defined as a group of two or more major commercial airports in a metropolitan region (de Neufville, 1986), and typically a major commercial airport was defined as an airport with at least two million passengers per annum.

One of the biggest challenges is to implement the operational interactions between airports in a MAR (Bonnefoy, 2008). Several researchers have addressed aspects of this problem, such as manage traffic allocation problems in a MAR (Hansen and Du, 1993) and the prioritization of arrival and departure routes in the terminal maneuvering areas of a MAR (Sidiropoulos et al., 2015). The MARs in existing large-scale studies often were defined by a spatial distance metric to estimate the airport catchment area, ranging from 50 km to 250 km: Airports within a fixed radius are aggregated as a MAR,

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starting with airports that have the highest numbers of passengers (O'Connor and Fuellhart, 2016; de Neufville, 1986; Bonnefoy, 2008; Hansen and Du, 1993; Sidiropoulos et al., 2015). However, there is an obvious caveat when using a spatial distance metric to define a MAR: Using the spatial distance assumes a homogeneous travel time from an airport to all concentric points at a given distance threshold. This view neglects the real infrastructure available for transportation and it is unlikely to capture the preferences and travel behaviors of passengers with a spatial distance based MARs (O'Connor and Fuellhart, 2016; Wittman, 2014). The reason for this simplification of distance is rather intriguing: When analyzing a large-scale network, it is difficult to obtain infrastructure data and service data for all regions. In fact, collecting infrastructure data for a single airport is often time consuming (Yang et al., 2016).

In this study we define the accessibility of an airport within a region based on a new metric: Temporal distance. This metric estimates how long it takes to travel between two airports, using either road network (by driving cars or taking taxis) or public transport (bus, lightrail, railway, subway, and tram). Our routing algorithms for finding travel itineraries between airports are based on the freely available data provided by OpenStreetMap (OSM), which has become an impressive source of worldwide public transportation and road network data, at a very high level of coverage (Neis and Zielstra, 2014). To compare the differences between spatial and temporal distance, we report the results of an initial experiment first. Fig. 1 presents the scatter plot between spatial distances using the haversine formula and temporal distances with our methodology for selected airport pairs. The haversine formula calculates great-circle distances between two points on a sphere from their longitudes and latitudes; while our methodology calculates the minimum travel time between two points by using either road network or public transport. Results are only shown for airport pairs with spatial distances less than 400 km and with temporal distances less than 4 h. Moreover, on the right-hand side of Fig. 1 we show a histogram of the travel speed between airports. There is no functional dependency and limited correlation between spatial distance and travel time between airports, which means that no fixed spatial distance can cover the real connectivity between different airports correctly. This is the major motivation for our study, analyzing the worldwide MAR network by using the temporal distance as a metric.

This paper is organized as follows. Section 2 provides the literature review on the state-of-the-art MARs analysis. Section 3 presents our methodology to construct MARs based on temporal distances, traveling either with road network or public transport. In Section 4, we present the results of worldwide temporal MARs. Finally, conclusions are drawn in Section 5.

2. Literature review

This section provides the literature review on the state-of-the-art analysis on MARs. Several researchers have studied MARs since the 1990s. A MAR was originally defined as a group of two or more major commercial airports in a metropolitan region (de Neufville, 1986). An inter-airport distance threshold of 50 km has been used for the definition of a MAR (Hansen and Weidner, 1995), a second criterion is that the Herfindahl concentration index for the airports in the region, which measures the degree to which passenger activity is concentrated is less than 0.95. The effects of improvements to airport ground access by non-automobile modes in a MAR were analyzed, with a case study of an extension of a Bay Area Rapid Transit rail

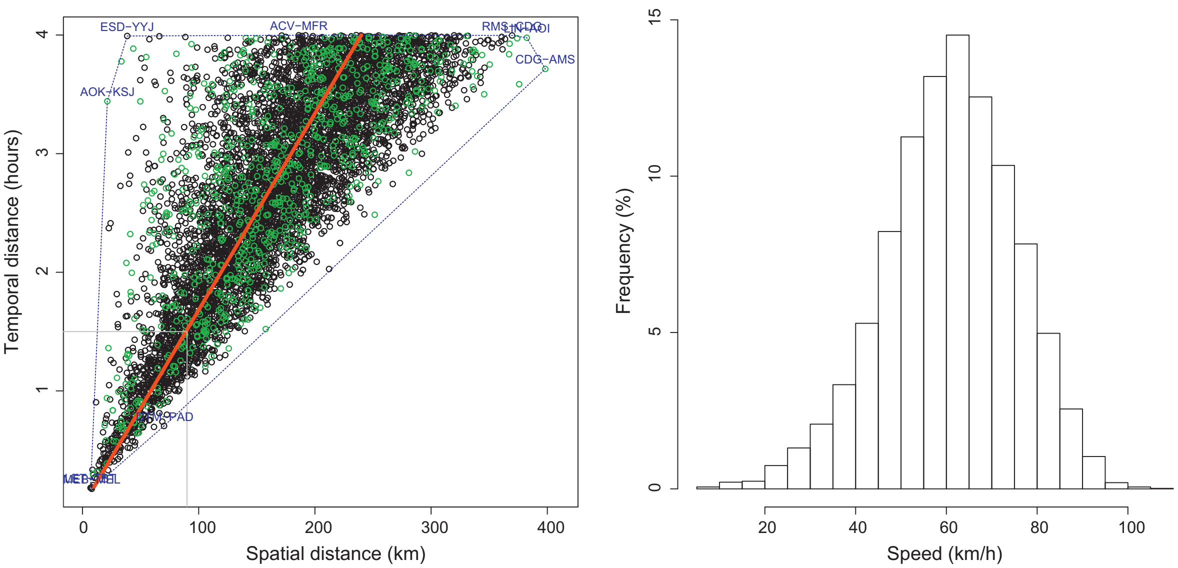


Fig. 1. Left: Scatter plot between spatial distances using Haversine formula and temporal distances with our methodology for selected airport pairs. Each circle represents one airport pair; circles shown in green colors are the airport pairs with direct flight connections, the blue dashed line represents the convex hull, the red diagonal line shows the travel time when the travel speed is 60 km/h. Right: Frequency distribution of travel speeds between airport pairs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

link into the San Francisco International Airport (Monteiro and Hansen, 1996). Results showed that the improvements to airport ground access would modestly strengthen the dominant position of the airport. Hansen and Du (1993) proposed a model of traffic allocation in a MAR, with an application to the San Francisco Bay Area. The empirical study on the operational efficiencies of 44 major U.S. airports showed that the characteristics of MARs may not strongly affect airport operational efficiency (Sarkis, 2000). The capacity and pricing choice of two congestible airports in a MAR have been studied in Noruzoliaee et al. (2015), analytical models with three privatization scenarios have been developed: Public–private duopoly, private–private duopoly, and private monopoly.

Sidiropoulos et al. proposed a framework for the prioritization of arrival and departure routes in the terminal maneuvering areas of MAR, with the London MAR (Heathrow Airport-LHR, Gatwick Airport-LGW, London City Airport-LCY, Stansted Airport-STN, and London Luton Airport-LTN) as a case study (Sidiropoulos et al., 2015). Nayak estimated the interaction between flight delay at one single airport and delay at the rest of national airspace system; factors affecting delays in nine MAR in the U.S. have been studied as well (Nayak, 2012).

Bonnefoy performed an in-depth multiple-case study analysis of 59 MARs in the world and developed a feedback model to capture the evolution dynamics of MARs (Bonnefoy, 2008; Bonnefoy et al., 2010). The roles of airports were categorized into primary and secondary airports: A primary airport was defined as serving more than 20% of the total passenger traffic in the MAR; while a secondary airport was defined as serving between 1% and 20% of the total passenger traffic. It was found that the evolution of MARs can be attributed to (1) the construction of new airports; (2) the emergence of secondary airports. The MARs in Asia-Pacific region belong to the former case; while the MARs in the U.S. and Europe belong to the latter case. The computation of MAR was based on traditionally used physical distance: All airports within 120 miles (around 193 km) of the city center were considered as MARs. Several restrictions were implemented in a follow-up filtering process: Airports serving less than 500,000 passengers per year and primary airports with less than two million passengers (in the year 2005) were not considered; Archipelago type airport systems resulting from the presence of islands or water areas were discarded as well. These strict filtering processes resulted in a rather small set of airports (451) and accordingly only 59 MARs worldwide. In this case, the analysis of MAR is incomplete and the roles of individual airports in the MAR might change when more airport candidates are considered. With the emergence and growth of low-cost carriers, the roles of small secondary airports are becoming more important, since low-cost carriers have been exploiting cheaper operations at underutilized secondary airports. Furthermore, large/hub airports have been suffering from heavy congestion and delay problems for a long time, diverting flights to secondary airports in the vicinity might help to mitigate these problems.

An initial step towards overcoming the limitation of a fixed spatial distance is presented in Wittman (2014). The definition of an airport catchment is based on U.S. Census Bureau primary statistical areas: Airports within an administrative boundary are defined as belonging to the same MAR. It was found that most U.S. regions lost access to air service during the study period (2007–2012). However, this definition of airport catchment has still several limitations. First, it was assumed that residents inside a region have the same accessibility to all airports. This is not true in reality, since different transportation options in a region provide different degrees of accessibility to the airports. Nowadays, passengers care more about door-to-door traveling, the degree of convenience to access one airport mainly decides which airport a passenger would select in a MAR. Second, it was assumed that residents in the periphery of a region are not allowed to travel to a nearby region with better accessibility. This is not the case in reality as well, since it was shown that passengers are willing to travel long distances to access an airport with low fares or attractive schedules (Suzuki et al., 2004), which often involves crossing administrative boundaries of states or regions.

Other related studies focus less on the network, and more on other aspects of MARs. Wu and Caves (2002) developed a model to simulate the aircraft rotation in a multi-airport environment. Schedule and punctuality data from an European airline was used as a case study. With a simulation experiment for the Des Moines International Airport in central Iowa (Suzuki et al., 2004) showed that most airlines have under-estimated the airport-leakage tendencies of travelers in single-airport regions and the revenues could be increased by reducing the airfares.

3. Methodology: a new perspective on MARs based on temporal distances

This section explains our methodology in detail. In several existing studies, MARs are identified based on a spatial distance metric to define the airport catchment area (between 50 km and 250 km). All airports within a fixed radius are aggregated into a MAR, starting with airports that have the highest numbers of passengers, see O'Connor and Fuellhart (2016), de Neufville (1986), Bonnefoy (2008), Hansen and Du (1993), and Sidiropoulos et al. (2015) for examples. However, this perspective neglects the real transportation infrastructure, and thus, does not capture the true time and cost of accessing airports (O'Connor and Fuellhart, 2016; Wittman, 2014). The reason for this simplification is the difficulty when looking at a large-scale network, of obtaining transport infrastructure data for all regions. In our study, we use the freely available dataset OpenStreetMap for the estimation of temporal distances. Section 3.1 describes how the temporal distance between any two airports worldwide is estimated. Based on the new temporal distance measure, we develop a methodology for extracting the worldwide MARs with air transportation data for the year 2015 in Section 3.2.

3.1. Temporal distance estimation with OpenStreetMap

In this subsection we describe the methodology and data used for estimating temporal distances. The goal is to extract the temporal distance between two airports for two transportation modes: road and public transit. In general, the travel time between two points can be queried by using publicly available routing services, such as, Google Maps or Baidu Maps. However, using these services has a few limitations, which are discussed below.

1. Automatically querying of routes between points is often forbidden or limited to a given number of queries per day. Since we have more than one million airport pairs in our study, this is not an option.
2. The coverage of different regions for these routing services is largely heterogeneous. While the public transit information for U.S. is very accurate, Google does not provide (reliable) public transit routing for many rural areas in specific countries.
3. Our own experiments showed that the routes (and time estimations) among different providers significantly differ, so combining results from different websites is not an option either (see Table 1).

Therefore, we created our own temporal distance estimates. In order to support worldwide routing, we build upon the freely available data provided by OpenStreetMap (OSM, URL http://planet.osm.org/). Started in 2004, OSM is a community project built by volunteer mappers, with the goal to create a free editable map of the world. Technically, it belongs to the area of crowd-sourcing, referring to how large groups of users can perform functions that are either difficult to automate or expensive to implement; OSM is one of the leading examples of such an effort (Haklay and Weber, 2008). While the information included in OSM can be incomplete, the amount of coverage in populated areas is very high (Neis and Zielstra, 2014). During the last 12 years, OSM data has become an accurate representation of the world, thanks to the development of cheap, yet accurate GPS devices and the spread of mobile phones. As part of the OSM effort, transportation modes throughout the world are being modeled, including stations and physical layout of streets/lines (Wandelt et al., 2016).

OSM describes map data using three graphical concepts: (1) nodes, (2) ways, and (3) relations. Nodes encode points on a map, for instance, way points, points of interest, stations, or crossing points of streets. The second concept, ways, are used to connect nodes into segments, which can be used for encoding rail/road infrastructure. The third concept, relations, combine nodes and ways into a collections of more complex objects. Examples for relations are urban transportation service lines or an important area of interest. In addition, one of the key concepts in OSM is the ability to tag all three types of conceptual elements with key-value pairs (so-called tag dictionaries). This annotation mechanism is used to describe names, speed limits, infrastructure properties, and others. We use the data collected by OSM to estimate the temporal distance between two points on earth as described below. It should be noted that our travel time estimation does not take into account actual traffic/schedule information, but estimates a lower-bound on the fastest travel time between two airports. While future work could take into account additional realistic traffic conditions, implementing this on a global scale is a very challenging task, as outlined in our discussion in the beginning of this subsection.

3.1.1. Estimating the temporal distance by road network

The project Open Source Routing Machine (OSRM) (Luxen and Vetter, 2011) has developed scalable techniques and implementations for routing vehicles with different speed profiles at continental scale based on Openstreetmap data. It is released as a small standalone server application (see URL http://project-osrm.org/). The major advantage of using OSRM is that we can directly exploit road-specific maximum speed information, which varies significantly among regions throughout the world. Therefore, the travel time estimation is usually very accurate. OSRM performs shortest path calculation based on contraction hierarchies, which allows queries at a planet scale. The server can be queried by providing an API with latitude/longitude of starting and end points. The result of a query is the route together with distance and driving time. We extracted the driving time for each airport pair in the network, by querying for the fastest driving connection between the latitude/longitude pairs of the given airports. The result is an estimation of the minimum free-flow time between the two points, without any information about road blocks, congestion, or other conditions.

Table 1
Travel time by road network or public transport between one airport pair: Tianjian Binhai International Airport (TSN) and Beijing Capital International Airport (PEK). Different search engines generate different results. Website assessed at 9 am on 17th August 2016. Note that the travel time might change slightly with different departure time of the day. In addition, construction projects, traffic, weather, or other events may cause conditions to differ from the map results as well.

Search engines	Distance (km)	Travel by car/taxi	Travel by public transport
Baidu maps	146.5	2 h	Approx. 3 h (subway line 2/3 + train + subway line 4/2 + airport shuttle)
Bing maps	149.4	1 h 36 min	8 h 29 min (airport shuttle + subway line 2 + bus + airport shuttle)
Google maps	154	1 h 53 min	4 h 8 min (subway line 2 + train + subway line 4/2 + airport shuttle)

Algorithm 1. Creating MARs based on temporal distances.

Input: Number of passengers per airport a in 2015 $pass(a)$, temporal distance threshold δ
Output: MARs assignment *assignment*
Let *airports* be the airports in *pass* sorted descendingly by the number of passengers
Let $assignment = \varnothing$
Let $seen = \varnothing$
for $a_1 \in airports$ **do**
  Add a_1 to *seen*
  for $a_2 \in airports$ **do**
    Let d_{car} be the temporal distance for taking a private car between a_1 and a_2
    Let d_{public} be the temporal distance for taking public transport between a_1 and a_2
    if $a_2 \notin assignment$ and $a_2 \notin seen$ and $min(d_{car}, d_{public}) \leqslant \delta$ **then**
      $assignment(a_2) = a_1$
      Add a_2 to *seen*
    end if
  end for
end for
return: *assignment*

3.1.2. Estimating the temporal distance by public transport

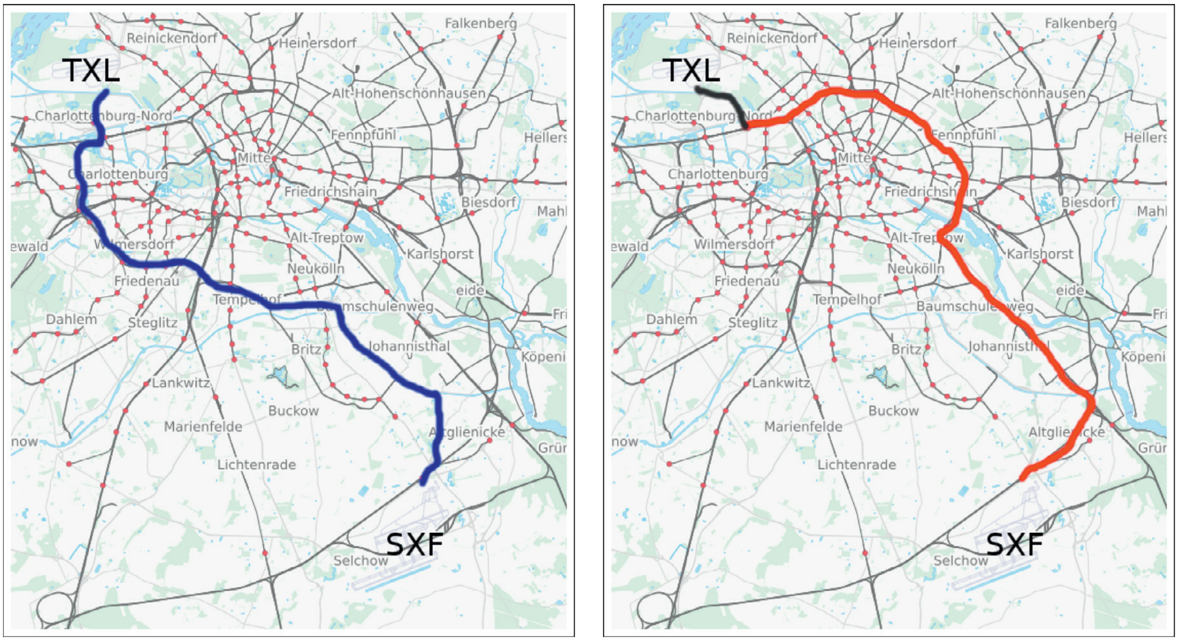
The estimation of a public transit distance is more challenging. First, we extracted several worldwide network layers from OSM: Subway, Lightrail, Railway, Bus, and Tram. The obtained geo-spatial network (with distance information between waypoints) was converted into a temporal network for estimating driving times along public transport routes. Here, we exploited the fact that most infrastructure elements in OSM are annotated with their maximum speed values. If the value was not present, we used the following default values: Subway = 50 km/h, Lightrail = 60 km/h, Railway = 100 km/h, Bus = 30 km/h, and Tram = 40 km/h. Next, we converted the infrastructure network (which describes waypoints between stations) into a logical network, by aggregating paths between stations; ending up with only the shortest temporal path. Finally, we created transition links between all five network layers as follows: If two stations are within 3 km distance, we connect them with a transition link at a walking speed of 3 km/h. The obtained multi-layer network is queried for shortest paths with latitude/longitude of starting and end points. For the computation of travel time, we add the following information about stop times: For subway, lightrail, tram, and bus we assume that a stop at a station takes 30 s, while a stop on a railway takes 2 min. When changing the travel modes, we add another penalty of 15 min. We extracted the traveling time for each airport pair in the network, by querying for the fastest connection between the latitude/longitude pairs of the airports.

In Fig. 2, we visualize the fastest connection on the road network and by public transit for the airport pair TXL (Berlin-Tegel Airport) and SXF (Berlin Schoenefeld Airport). The temporal distance between the two airports is the minimum travel time, which is traveling on the road network in this case.

3.2. MARs generation

We create the MARs for the year 2015, based on the flight leg data from the Sabre Airport Data Intelligence (ADI, http://www.airdi.net). The leg is stored by months and contains the following information: Source/destination airports and the number of passengers who used that flight leg in one month. We sort the airports according to the total number of passengers in the year 2015 (inbound + outbound passengers). We iterate over all airports in the descending order of passengers and query the temporal distance to all other airports. Once the distance to the larger airport is below a threshold, we assign that airport as belonging to the MARs of the larger airport. In addition, we mark the airport as being assigned and do not try to reassign it in the future. The algorithm is formalized in Algorithm 1. After execution of the algorithm, variable *assignment* contains a mapping from airports to their main airport in the MAR.

The process of deriving MARs with Algorithm 1 is visualized in Fig. 3 with 31 domestic airports in Germany as a running example. The ranking of airports by number of scheduled departures in 2015 is as follows: FRA, MUC, TXL, DUS, HAM, STR, CGN, HAJ, NUE, SXF, BRE, DRS, LEJ, FMO, HHN, FKB, DTM, NRN, SCN, FDH, PAD, RLG, ERF, GWT, LBC, MHG, BGN, HDF, KSF, ZCD, and BWE. We start with all these airports depicted in Fig. 3(a). The highest ranked airport is FRA. Two airports can be reached from FRA within 1.5 h temporal distance: MHG (around 40 min) and HHN (slightly more than one hour). Both airports are recorded in variable *assignment* as belonging to the MAR center FRA and added to the set *seen* of visited airports (Fig. 3(b)).



a) **By road network**: Following the three major inner-city highways (A111, A100, and A113, highlighted in blue) makes the connection from TXL to SXF by car or taxi very efficient. The total travel time is around 30 minutes, more than twice as fast as public transit.

b) **By public transport**: From TXL to S Beusselstrasse with airport shuttle bus TXL (gray), then switch to the Berliner S-Bahn (red, lightrail) for three consecutive trips with S8, S41, and S42. Total transportation time: Around 1 hour and 5 minutes.

Fig. 2. Visualization of different transportation modes from TXL (Berlin-Tegel Airport) to SXF (Berlin Schoenefeld Airport). Both transportation modes take significantly different routes and require very different travel times: Less than 30 min (a) vs. more than one hour (b).

Next, we process the second-highest ranked airport MUC: Fig. 3(c). Since no airports are reachable within 1.5 h, we proceed with TXL. SXF can be reached from TXL within around 30 min in the best case. Therefore, we group SXF together with TXL: Fig. 3(d). The process is executed until all airports are assigned.

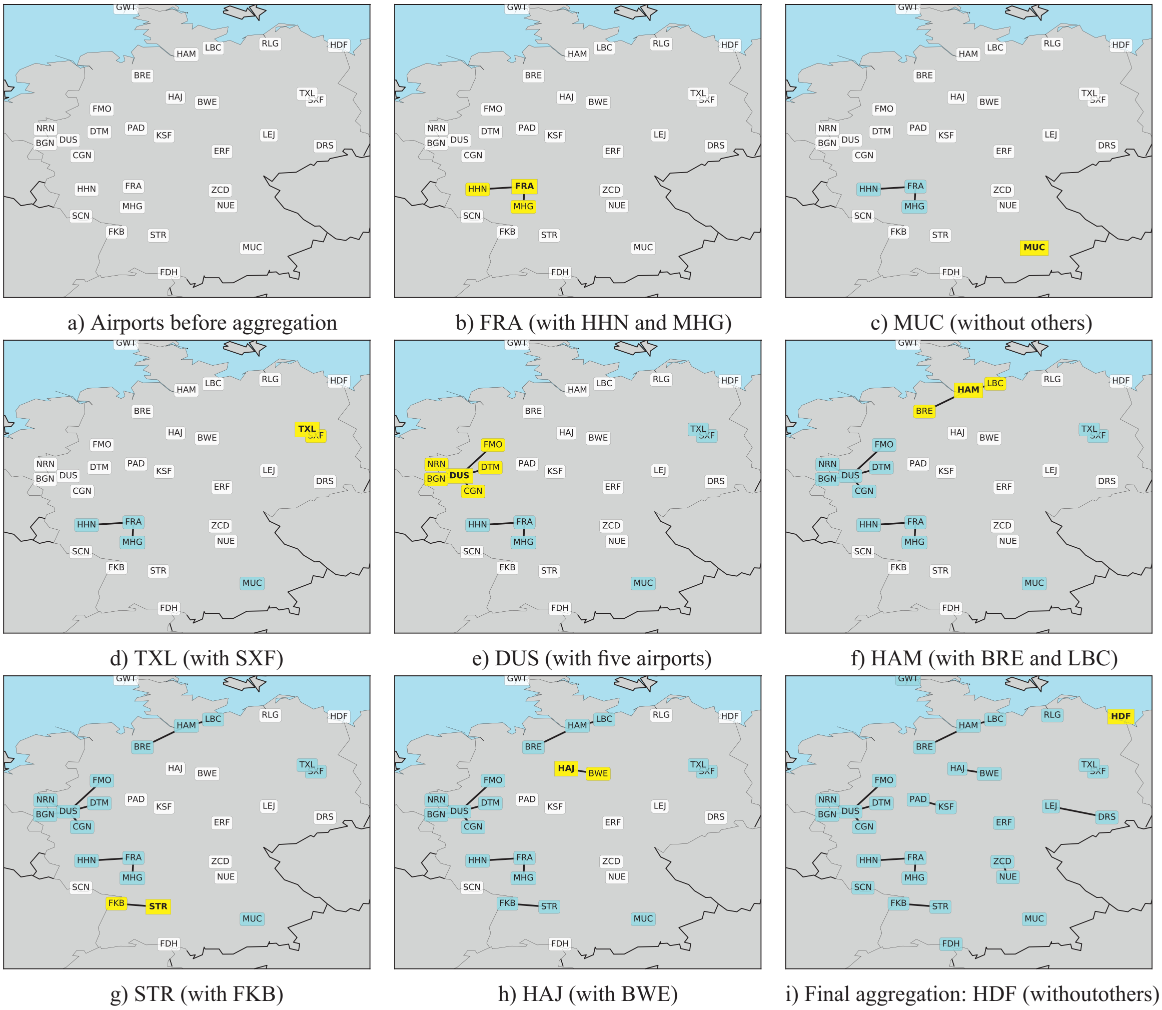
4. Results: temporal-distance MARs in global air transportation

In this section, we perform an analysis of global MARs based on temporal distance, and compare the results against those obtained by using spatial distance. Our analysis is based on a set of 3148 airports, for which we have air passenger traffic data (provided by Sabre ADI) and spatial information (collected online). Opposed to related studies, we did not apply any filters on these airports.

The majority of experiments in this section is based on the temporal distance of 1.5 h and a spatial distance of 90 km, as identified in Fig. 1. Section 4.1 discusses general properties of the MARs network and investigates the largest MARs in the world. We lay a particular focus on reporting similarities and dissimilarities between spatial and temporal clusterings. In Section 4.2, we further analyze the most frequent distribution of airport types in MARs, distinguishing primary, secondary, and tertiary airports. Finally, in Section 4.3 we consider the mix of destinations from airports in a MAR.

4.1. Network properties of global MARs based on temporal distances

Fig. 4 (top) shows an overview on global MARs for the year 2015 with a temporal threshold of 1.5 h, i.e., an airport only belongs to a MAR, if it is within 1.5 h of driving/public transport to the main airport in the MAR. The size of a MAR is the number of its component airports. The visualization in Fig. 4 (bottom), with a spatial threshold of 90 km, makes it possible to compare the largest MARs identified by both aggregation strategies. First of all, it can be seen that the spatial distance aggregates more airports into MARs, leading to larger MARs: While for the temporal distance of 1.5 h only four MARs with more than 6 airports exist (LHR, BRU, JFK, BOS), using the spatial aggregation leads to nine MARs with more than six airports inside. Most notably, using the spatial distance, we obtain several large MARs in Alaska (e.g., OOK, BET, EMK) which are not identified as such based on temporal distance. The reason is that these airports are not well connected to each other (except from using flight connections) and thus should not be clustered as MARs. Similarly, in other regions, we find that the spatial distance often identifies many small island airports as MARs (e.g., BOB, HDR, and OGG), while these islands are only connected by flights. We can also find similar inaccessible regions on the land. We conclude that, when applied at a global scale,



a) Airports before aggregation
b) FRA (with HHN and MHG)
c) MUC (without others)
d) TXL (with SXF)
e) DUS (with five airports)
f) HAM (with BRE and LBC)
g) STR (with FKB)
h) HAJ (with BWE)
i) Final aggregation: HDF (withoutothers)

Fig. 3. Visualization of Algorithm 1 for the domestic airport network of Germany. The current main airport (bold and rectangular border) and all airports that can be reached within 1.5 h are highlighted in yellow color. Processed airports are highlighted in blue, while open airports are indicated with white color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

use of temporal distance yields a substantially different and more realistic set of MARs. Table 2 show the number of MARs in each continent, grouped by the size of the MAR, i.e., the number of airports. Fig. 5 presents the top six largest MARs.

Our construction of temporal MARs depends on the threshold of temporal distances between airport pairs. It is interesting to check how the size of MARs would change when the thresholds change. Fig. 6 (a) shows the sensitivity analysis for the top six temporal MARs with different temporal thresholds, ranging from 0 to 2.5 h. The transportation options could be road network or public transport (railways, subways, light rails, tram, and buses). A general trend is that with the expansion of the temporal distance threshold, the sizes of MARs increase gradually. Note that there are two exceptions: When the temporal threshold reaches around 1.6 h, the size of temporal MAR for Brussels Airport (BRU, shown in blue dashed line) decreases suddenly, because the airport is absorbed into Amsterdam Airport Schiphol (AMS). It is not surprising that more airports are merged into the MARs as the threshold increases, however, some airport members of a MAR could also be absorbed by nearby MARs, whose hub airports have higher passenger traffic. Fig. 6 (b) shows the sensitivity analysis for the top six spatial MARs with different distance thresholds, ranging from 0 to 150 km.

Air transportation networks are often analyzed regarding the complex network properties (Shang et al., 2015; Sun and Wandelt, 2014). Fig. 7 visualizes the scatter plot of three centrality measures (degree centrality, betweenness centrality, and closeness centrality) for temporal distance against spatial distance. A MAR is plotted on the diagonal line, if its centrality value is identical for temporal and spatial distance, with a speed of 60 km/h. We find that the centrality measures are rather similar in both types of MARs aggregations. So the effect on the network structure, from a topological point of view, is not significant.

Fig. 8(a) shows the frequency distribution of temporal distances for the top six largest MARs, traveling from each non-hub to the hub airport. As indicated by the red median lines, most hub airports can be reached within 0.5–1.5 h in the MARs. The temporal distances vary significantly from one MAR to another, for instance, the median temporal distance for BRU (Brussels

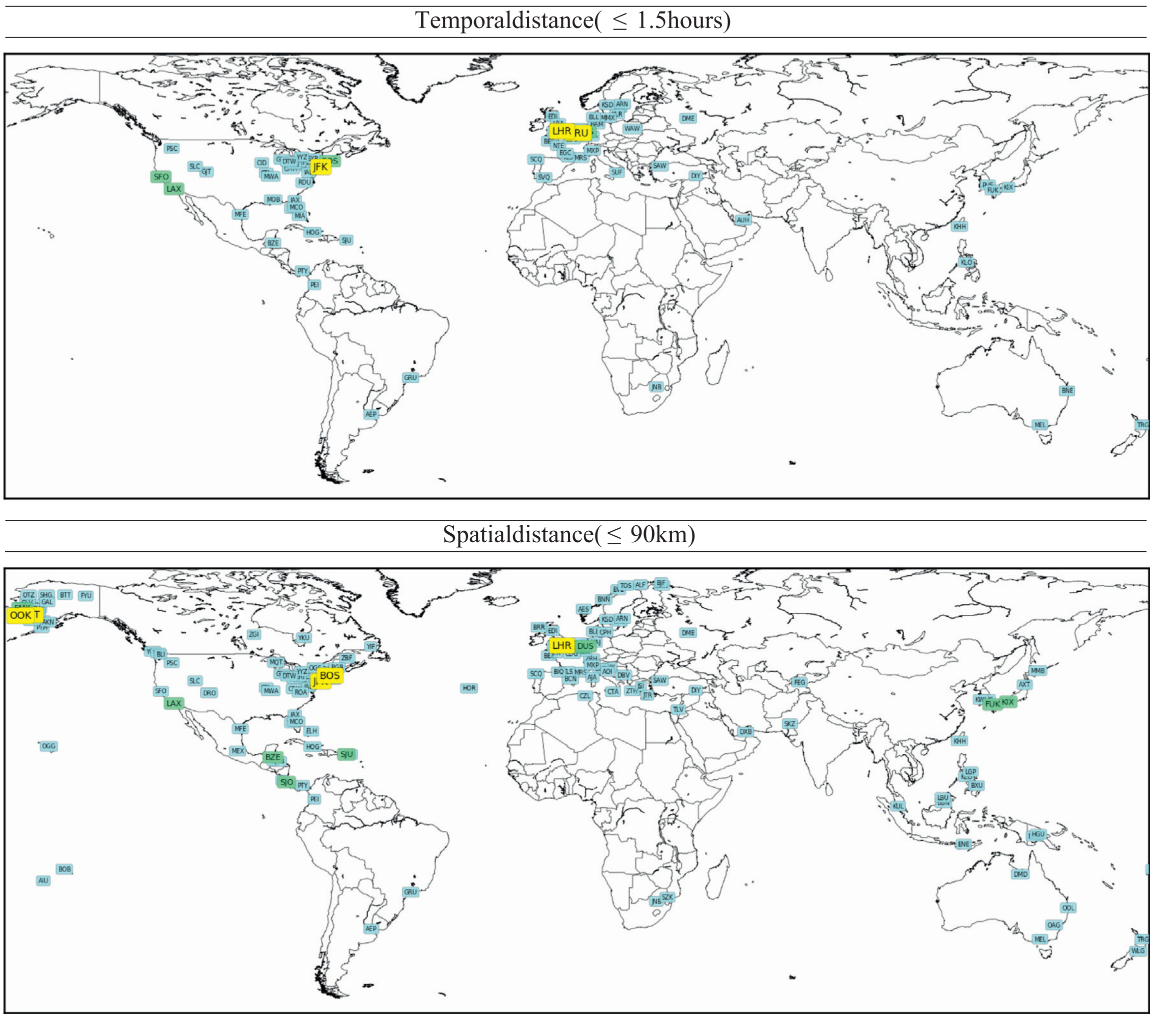


Fig. 4. An overview on global MARs based on temporal distance proposed in our study (1.5 h, top) and traditional spatial distance (90 km, bottom). MARs with 3–4 airports are visualized with blue color, 5–6 airports with green color, and more than 6 airports with yellow color. It can be seen that with the spatial distance, more and larger regions are identified as MARs compared to using temporal distance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
MARs size distribution: Temporal distance (1.5 h). The number of MARs by number of airports and continent of the MAR is shown.

Continent/ Nr. of airports in MAR	1	2	3	4	5	6	7	8	9	10	11	12	SUM
Africa	297	13	1	0	0	0	0	0	0	0	0	0	311
Asia	677	49	5	3	0	0	0	0	0	0	0	0	734
Europe	319	59	20	6	1	0	0	1	0	0	1	0	407
North America	630	99	20	8	2	1	0	1	0	0	0	0	761
Oceania	200	23	3	0	0	0	0	0	0	0	0	0	226
South America	211	22	2	1	0	0	0	0	0	0	0	0	236
SUM	2334	265	51	18	3	1	0	2	0	0	1	0	2675

Airport) is almost twice as high as for LAX (Los Angeles International Airport). Fig. 8(b) presents the frequency distribution of spatial distances for the top six largest MARs. The red median lines show that most hub airports are 50–80 km away from the non-hub airports.

4.2. Clustering of MARs according to primary/secondary configuration

In a MAR, we categorize the component airports into three classes: Primary airports (serving more than two million passengers in the year 2015), secondary airports (with at least 100,000 passengers but less than two million passengers), and

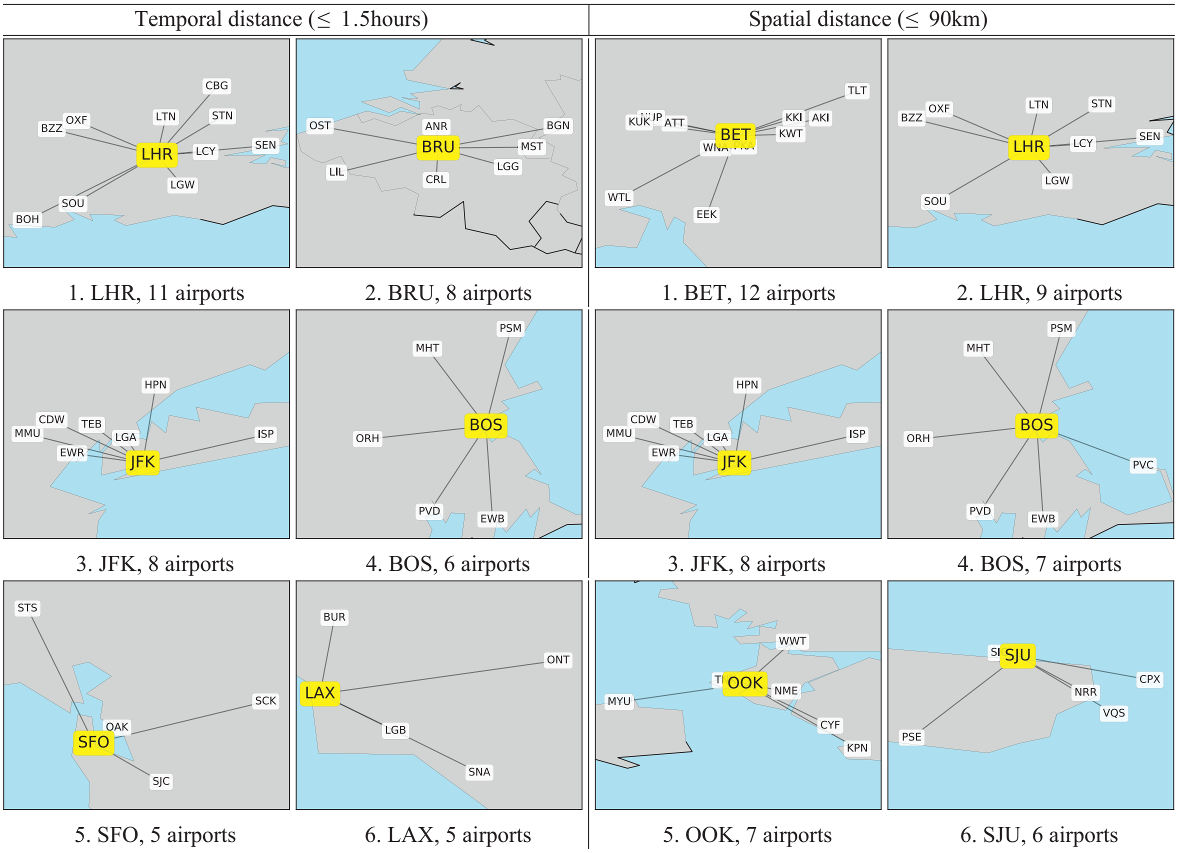
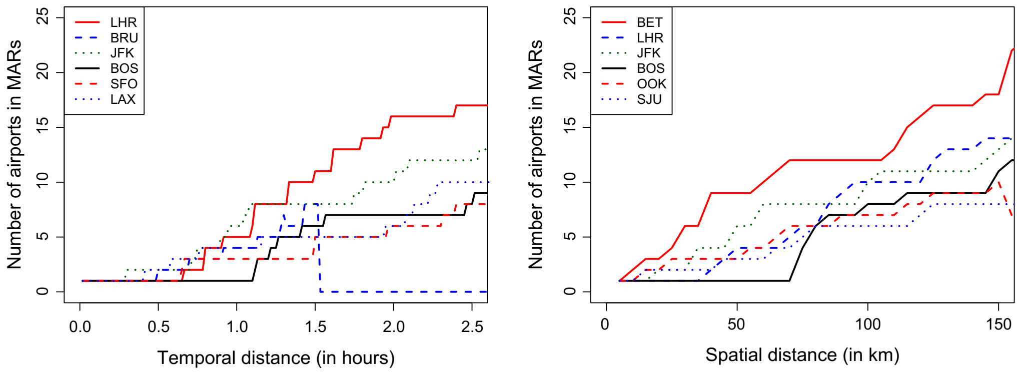


Fig. 5. The top six largest MARs ranked by the number of component airports for the temporal distance (left) and spatial distance (right).



(a) Top six temporal MARs

(b) Top six spatial MARs

Fig. 6. Sensitivity analysis for the top six MARs based on temporal distances (a) and spatial distances (b). Different thresholds are shown: The maximum travel time is 2.5 h, using either road network or public transport; while the maximum spatial distance is 150 km. It can be observed that with the expansion of the distance thresholds, the sizes of spatial MARs increase much faster than temporal MARs, without considering how two airports can be connected in reality. This clearly indicates that the temporal distance proposed in our research is more realistic and appropriate for studying multiple airport markets.

tertiary airports (with less than 100,000 passengers). Note that the threshold of two million passengers for primary airports is consistent with (Bonnefoy, 2008). We are interested in how similar the airport classes are in different MARs across world regions. The following two steps are performed: (1) For each MAR, we compute the percentage of each airport class. (2) With the percentages of airport classes as the input data, we cluster the MARs with similar composition of airport classes using k-means algorithm.

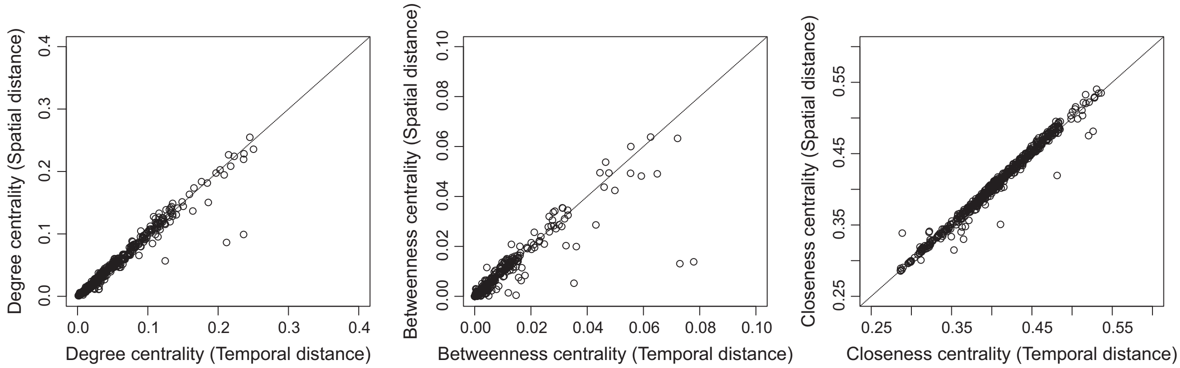
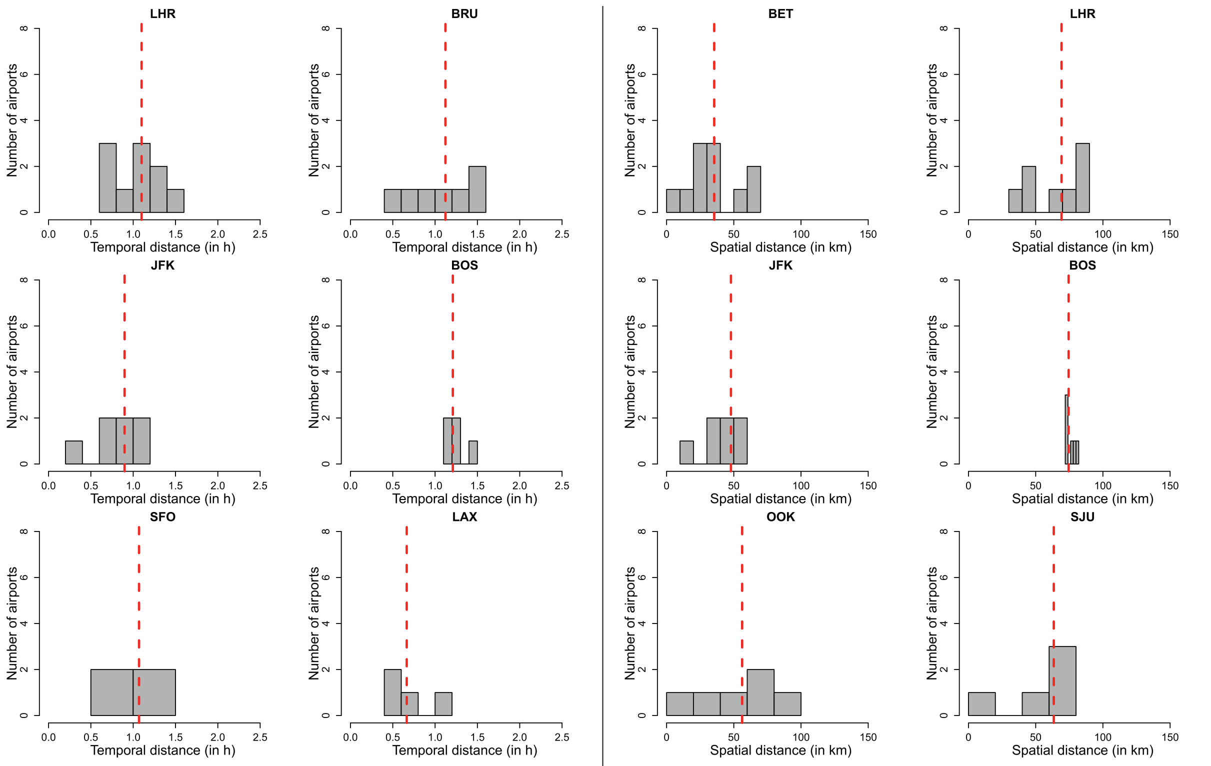


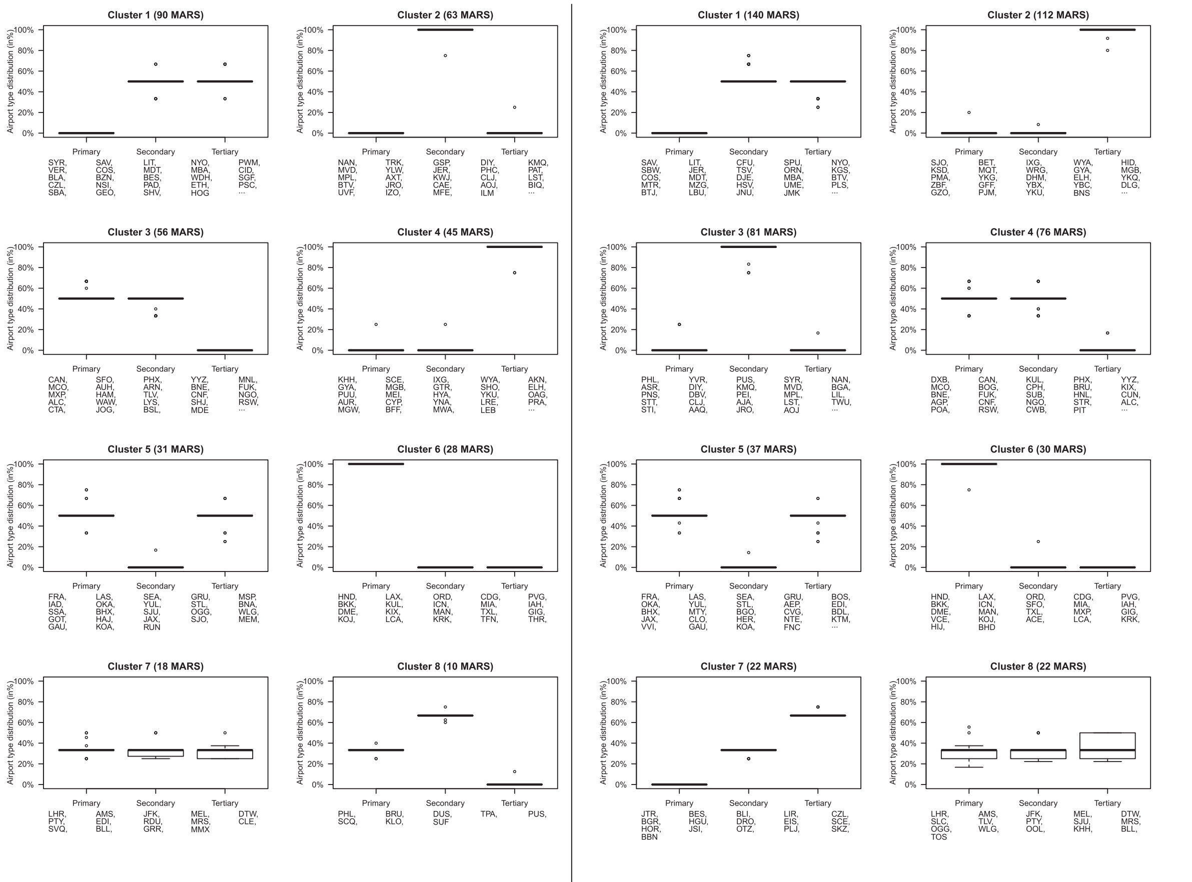
Fig. 7. Scatter plot of three centrality measures: Degree centrality (left), betweenness centrality (middle), and closeness centrality (right), with temporal distance against spatial distance for global MARs. A MAR is plotted on the diagonal line, if its centrality value is identical for temporal and spatial distance, with a speed of 60 km/h. It can be seen that the centrality measures are strongly correlated in both types of MARs aggregations, if the speed is chosen appropriately.



(a) Temporal distance (≤ 1.5 hours) (b) Spatial distance (≤ 90 km)

Fig. 8. Frequency distribution of temporal distances (left) and spatial distances (right) for the top six largest MARs, traveling from each component airport to the hub airports. Red lines represent the median distances. It can be seen that the temporal distance varies significantly from one MAR to another. For BRU (Brussels Airport) the median temporal distance is more than twice as high as for LAX (Los Angeles International Airport). In the top six largest MARs with spatial distances, most hub airports are 50–80 km away from the component airports. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 9 presents the clustering results for global MARs based on temporal distance (left) and spatial distance (right). For each cluster, we show the distributions of airport types with box plots, with outliers plotted as individual points. The flat shapes of the majority of the box plots indicate low intra-cluster variability. Among 341 MARs based on temporal distances, approx. 25% belong to Cluster 1, which has very few primary airports and roughly equal shares of secondary and tertiary airports; 18% of the MARs have equal share of primary and tertiary airports (Cluster 2); and 16% of the MARs are mainly com-



(a) Temporal distance (≤ 1.5 hours)

(b) Spatial distance (≤ 90 km)

Fig. 9. Clustering of MARs worldwide using k-means algorithm, with default value of the input parameter $k = 8$ for temporal distance of 1.5 h (a) and for spatial distance of 90 km (b). For each cluster, the distributions of airport types with box plots are shown. Below each sub-figure, top 24 MARs serving the largest numbers of passengers in the year 2015 are listed as well.

posed of primary and secondary airports (Cluster 3). It is interesting that most MARs based on spatial distance have similar clustering patterns.

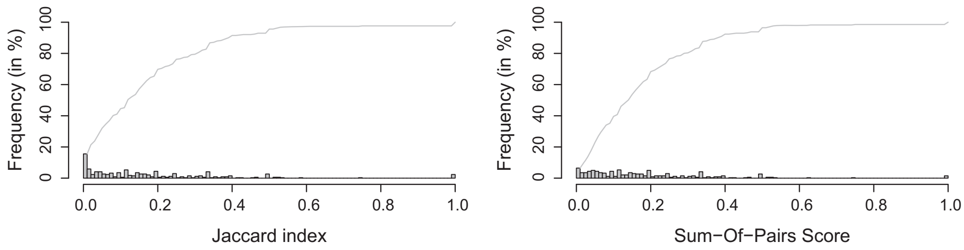
Note that k-means algorithm uses the Euclidean distance and variance for clustering; the results might change with different input parameters of k. In this research, we use the default value of $k = 8$ when performing the clusters of MARs. We also clustered the MARs using DBscan, and obtained similar sizes of clusters (8–10).

4.3. Analysis of destination overlap inside MARs

In order to explore the dynamic dimensions of the complex mix of destinations served from each airport in a MAR (O'Connor and Fuellhart, 2016), we compute three measures: (1) Jaccard index between all destinations of all airports in a MAR. (2) Sum-of-pairs based on multiple sequence alignment in bioinformatics. (3) Coverage of destinations for hub airports and non-hub airports separately in a MAR.

4.3.1. Jaccard index for all airports in a MAR

First, we computed the Jaccard index between all destinations of all airports. The Jaccard index is a statistical measure for the diversity of sample sets, defined as the fraction of the size of the intersection and the size of the union of the sample sets. Formally, given a set of airports $a_1, \ldots, a_n$ in a MAR, and let $dest(a_i)$ denote the set of destinations of airport a_i, the Jaccard coefficient is the result of $\frac{|\bigcap_{1\leqslant i\leqslant n} dest(a_i)|}{|\bigcup_{1\leqslant i\leqslant n} dest(a_i)|}$, i.e., the number of shared destination served by all airports divided by the total number of destinations. This measure yielded an overlap of zero for many MARs in our dataset; see Fig. 10(a). The reason is that it is rare that even a single destination is served by all airports in a MAR, and thus, the numerator is frequently zero. Therefore, it is difficult to distinguish, whether the Jaccard index is not applicable in our case, or whether the overlap between destina-



(a) Jaccard index (b) Sum-Of-Pairs

Fig. 10. Frequency distribution of destination overlap between airports in all temporal MARs, according to Jaccard index (left) and sum-of-pairs (right). The gray curve visualizes the cumulative frequency distribution. Many MARs have the Jaccard index of zero, while most MARs have a rather small sum-of-pairs: Around 90% of all MARs have an estimation of less than 0.46, while the majority has values less than 33%.

tions is really so small. Essentially, one should keep in mind that the Jaccard index is often used for the case of two input sets only.

4.3.2. Sum-of-pairs for all airports in a MAR

In this study, we build on the sum-of-pairs score as follows. First, we compute the set of all destinations of MARs. Second, for each destination d and each pair of airports (a_1, a_2) in the MARs, we compute whether a_1 and a_2 serve destination d. If yes, we increment a counter (initialized to 0) by 1. Finally, we normalize the counter by dividing it through the number of destinations, as well as, the total number of airport pairs, $\frac{n*(n-1)}{2}$ for n airports in the MARs. The resulting value is an estimation for the overlap of the destination.

We show the results of this overlap measure on a small toy example with three airports $a_1, \dots, a_3$ and seven destinations $d_1, \dots, d_7$. The assignment of airports to destinations is as follows.

$$dest(a_1) = [d_1, d_3, d_4, d_5, d_7]$$
$$dest(a_2) = [d_5, d_6]$$
$$dest(a_3) = [d_1, d_2, d_3, d_4, d_6]$$

When we compute the similarity between the destinations of airport a_1, airport a_2 and airport a_3, we have a set of destinations $[d_1, d_2, d_3, d_4, d_5, d_6, d_7]$. Destination d_1, is served by airport pair (a_1, a_3), but neither by (a_1, a_2) nor (a_2, a_3). Thus, for destination d_1, the counter is increased to 1. Destination d_2 is only served by a_3 and thus none of the three possible airport pairs contributed to the counter, which remains at 1. Following the same procedure, we add one to the counter for d_3, d_4, d_5, and d_6. Thus, the counter is 4, and the normalized value of the counter is $\frac{4}{3*7} \approx 20\%$. Note that the generalized Jaccard index in this case would simply yield 0, since none of the destinations is served by all three airports.

The frequency distribution of this metric across all MARs is shown in Fig. 10. It can be seen that most MARs in our dataset have a rather small overlap: Around 90% of all MARs have an estimation of less than 0.46, while the majority has values less than 33%. The few MARs with very high overlap estimations usually belong to small MARs, where all airports in the MAR are connected to the same hub airport, but have no other connections. One interesting case is the MAR for Lanzarote and Fuerteventura (airports: ACE and FUE): This MAR has an estimated overlap of 68%. Further analysis of these two airports reveals that both of them are connected mainly to overlapping connections in Western Europe.

4.3.3. Coverage of destinations for hub airports and non-hub airports separately in a MAR

The previous two destination overlap indexes, the Jaccard index and sum-of-pairs, do not distinguish hub airports and non-hub airports in a MAR. It would interesting to check how the destination overlap would change, depending on the roles of airports. Fig. 11 compares the coverage of destinations for hub airports and non-hub airports in MARs which have at least two airports. In our study of the 341 MARs: 20% of the hub airports can reach all destinations of their MARs; 70% of the hub airports can reach 80%; 91% of the hub airports can reach 60%. On the other hand, without hub airports, only 5.5% of the non-hub airports can reach all destinations of the MARs; 12.8% of the non-hub airports can reach 80%; 29.6% of the non-hub airports can reach 60%. We can conclude that the services provided by the hub airports are rather complete, even without the presence of non-hub airports in the MARs.

5. Conclusions

This paper addresses the problem of systematically identifying MARs without invoking ambiguous geographic constructs such those employed in the literature. Such previous studies have defined MARs as, for example, two or more significant airports that serve commercial passenger traffic in a metropolitan region. Such a definition depends on a pre-defined set of regions and also an objective criterion for whether an airport serves commercial traffic in a region. However, there are var-

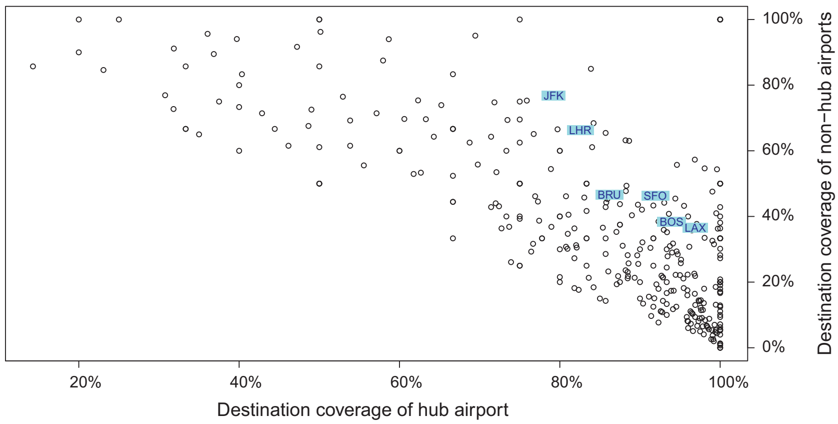


Fig. 11. Comparison of the destination coverage for hub and non-hub airports in temporal MARs, top six temporal MARs with the largest number of component airports are marked out. The majority of right-skewed data points indicate that the services provided by the hub airports are rather complete, even without the presence of non-hub airports in the MARs.

ious ways of delineating metropolitan regions, even for a given country. For example, the US Government defines Urban Areas, Metropolitan Statistical Areas, Micropolitan Statistical Areas, and New England City and Town Areas. The Regional Plan Association, and non-governmental organization, has also delineated Megaregions in the US. Even given a definition of a metropolitan area, existing data do not enable us to define what airports serve this area. There are many occasions in which residents of a given area may use an airport not located within the confines of that area, but the data do not clearly show where the true origins or destinations of passengers using a particular airport. In this paper, we propose methods of identifying MARs that do not depend on arbitrary geographic boundaries or the ambiguous notion of an airport serving an area. Rather our definitions are based purely on a measure of distance between airports and widely available data on total airport passenger traffic. Also, since our approach uses data that is available for airports throughout the world, it is able to define MARs all over the world in a consistent manner. Finally, compared to previous studies that use inter-airport spatial distance, here we use temporal distance, which is clearly the more appropriate measure.

The key contributions of this research are as follows.

1. We propose a new metric to assess accessibility between any two airports in the world: Temporal distance as induced by traveling either by road or public transport. Instead of the traditionally used spatial distance metric, we use a newly proposed temporal distance to build a network of global MARs. Our temporal distance estimation is based on the freely available data from OpenStreetMap and has the capability of worldwide routing.
2. The temporal distance metric is used to derive a MAR network for the year 2015, based on the worldwide air ticket data from Sabre Airport Data Intelligence. We analyze the distribution of MARs and also the distinguished largest MARs in the network. We find that the MARs often have significantly different speed profiles for their airports. Clustering the MARs by sizes of the member airports reveals that the majority of MARs has a rather mixed structure of primary, secondary, and tertiary airports. Moreover, we report network properties for the MAR network and discuss how far they differ from the traditional spatial distance approach.
3. We explore the mix of destinations from airports in a MAR. Identifying three measures of overlap (Jaccard index, alignment-based sum-of-pairs, and coverage separation between hub and non-hub airports), we find that most MARs have a rather small destination overlap and so that many services provided by these airports are often complementary. On the other hand, we find that there is a strong dependence of airports in a MAR on their hub airport, which usually has service most, but not all, of the MAR destinations.

Our results show that the global topological properties on MARs based on temporal and spatial distance are not significantly different. This can probably be explained by a large number of MARs with only one (or two) airports inside, which are often identical regardless of whether temporal and spatial distance is used. Only for MARs with more airports (and more infrastructure developed between them), we can see the differences clearly. While the categories of the primary/secondary classification are indeed similar, there are several airports which belong to different classes regarding spatial and temporal distance. As we can see in the visualization in Fig. 5, the assignments of MARs are different even for non-extreme cases, such as LHR and BOS. To summarize, the key point of our method is to have a global inventory of MARs based on temporal distance, together with the conformation that some properties are similar, while others are not, when compared to MARs based on the rough proxy of spatial distance. The identification of these (dis)similarities is the major contribution of our work.

Below, we discuss a few limitations of our approach, which could lead to future work on MARs:

1. Data preparation challenges: Methods based on spatial distance can be easily computed by haversine distance, given latitude/longitude of each airport. Managing hundreds of GB for the worldwide transportation infrastructure required us to use dedicated hardware, while still taking several days of pure computation. However, traditional methods based on spatial distance always need some post-filtering. We are not aware of any standard method for this step established in the literature. Mostly, they include (a) cutting of small airports based on passenger thresholds, (b) eliminating airports on hand-collected islands, and (c) taking into account administrative borders. These filtering steps are essentially necessary because no (large-scale) infrastructure data is available. In this study, we showed that infrastructure data can be made available based on Openstreetmap.
2. Reproducability of MARs: Methods based on spatial distance will compute the same MARs independent of the infrastructure, and are therefore reproducible (as long as the same post-filter steps are performed). Our approach, on the other hand, will compute different MARs once the infrastructure changes; which is usually rapidly modeled and reflected in Openstreetmap. We think that this is actually an advantage, since the MARs do change over time, with the establishment of new ground transportation infrastructure. High-speed rail, for instance, is changing the game completely in China, with major HSR stations being located directly at airports (e.g. Shanghai). Therefore, we argue that filtering-based methods also need to be adapted in these cases, if they are supposed to reflect real-world connectivity. With our technique, based on infrastructure data and reachability computation, we are always reflecting the current state of the world, as represented in Openstreetmap. Moreover, we believe that, based on infrastructure data, you can even perform realistic simulations of case-studies, for instance, how does a new railway line change the accessibility of airports; something that cannot be done with spatial techniques.
3. Parameter estimation for temporal distance: Throughout this study, we assume a homogeneous composition of passengers traveling between airports. This assumption is a simplified view, since in reality people living around airports have different preferences for choosing transportation modes, depending on age, mobility, and travel purpose. Neglecting these preferences can be understood as estimating a best-case connecting time, where all passengers use the fastest available connection. For instance, elderly people are known to be less focused on travel time and pay higher attention to comfort. Thus, once these people travel, a slower connection with public transit might not be acceptable for them. Similarly, people without a car will have to use public transit, which could shift the MAR regions from the perspective of these passengers. Future studies could take into account more realistic passenger composition models. The goal of our study can be understood as estimating a best-case connecting time. In order to perform future studies with realistic compositions of passenger groups, several challenges need to be overcome. First, a large quantity of data is required to perform such an analysis at the worldwide scale. While it might be possible to obtain city-level data for many cases, one actually needs data below city resolution, in order to accurately estimate population density, population demography, and their induced usage of transportation modes. The Population Grid mentioned above is a first step in this direction; and future releases are announced to contain more demographical data. A second challenge comes with the expenses of computational experiments. Assuming a homogeneous passenger group, the worldwide experiments performed in this study required days of computing power, essentially for determining shortest connection times. Further increasing the complexity of the passenger and travel model will likely render it unfeasible to compute the MAR at a very large scale, given todays hardware.
4. Analysis of accessibility: In our present study, we estimate the distance between two airports by the minimum driving time, taking into account car and public transit. This approach is more realistic than the state-of-the-art, which usually makes use of line-by-sight distances at larger scale. With this view, we can answer questions such as how long it takes (approximately) to travel from one airport to another, in case of disruptions or congestion. However, this is only one possible view on the function of MARs, which focuses on the replaceability of airports inside networks, i.e., seeking for alternative airports in case of disruptions. Other views may focus on the accessibility of MAR airports by actual or latent passengers. In order to compute an estimation of the actual access time, other publicly available datasets, such as Population Grid http://sedac.ciesin.columbia.edu/data/collection/gpw-vcan be used to (a) identify the population density inside a MAR and (b) compute the individual access time to airports using the methodology in our study. With such an approach, it would be possible to accurately estimate the access times and further judge the competition and cooperation effects inside a MAR. Computing the access time on a grid-like network with high resolution poses tremendous challenges on the computing power; especially on a world-wide scale. Nevertheless, we believe that the evaluation of actual access times to airport is an important step for future work, which can lead to different insights on MAR structures.

Despite these limitations, we think that our work is the first and initial attempt to derive the worldwide MARs based on infrastructure, and we expect that other researchers pick up on our work and extend it.

Our study contributes towards a better understanding of realistic MARs networks, and eventually leading to the design of better inter-modal networks (Ghane-Ezabadi and Vergara, 2016; Yang et al., 2016) and increased network resilience (Edrissi et al., 2015). In the current study, when computing the temporal distances between two airports using public transport, maximum speed values for five transportation options have been considered: Bus, lightrail, railway, subway, and tram. Future work could take into account several other factors as well, such as ticket prices, schedules and levels of comfort with different transportation options. Moreover, the concept of MAR facilitates analyzing the resilience of air transport systems: If an airport in a MAR was disabled, we could check how effectively other airports in the MAR could pick up the slack. Airport substitution in a MAR is a way to mitigate supply demand imbalances; for example, rerouting flights from airports with high delay to airports with lower delay. Therefore, several related research areas can exploit our temporal distance metric to obtain more accurate and realistic analysis of air transportation in general.

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