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A new generalized travel cost based connectivity metric applied to Scandinavian airports

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A R T I C L E I N F O

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A B S T R A C T

This article proposes a new, generalized travel cost based method to operationalize network accessibility provided by airports. The approach is novel as it integrates features of network topology with multiple quality aspects of scheduled air transport services into one metric. The method estimates generalized travel costs for the full set of feasible travel paths between an airport and all network destinations. Rooftop modeling accounts for schedule delay and isolates the most cost-efficient travel paths per O-D relation. Respecting the assumed arrival time preference of passengers and adjusting for destination importance, connectivity scores are derived. The method is then applied to explore changes in the global connectivity pattern of Scandinavian airports from 2004 to 2018. The results suggest distinct spatial differences throughout the network, but less pronounced in size than suggested by popularly applied connectivity measures. Findings also highlight the importance of the geographical location as a determinate of an airport's connectivity.

1. Introduction

Connectivity, loosely defined as the degree to which a network node (airport) is connected to the rest of the network (Burghouwt and Redondi 2013), has gained wide recognition as a key concept among transport policymakers. Owing to the economic benefits of air transport services, institutions implement the notion as a planning tool to enhance regional development, reduce spatial disparities, generate trade, and promote tourism (EC 2015; Schlumberger and Giovannitti 2016; FAA 2018). In air transport research, the concept has recently been applied to study the properties of air transport networks (e.g., Cattaneo et al. 2017), the competitive position of airlines and airports (e.g., Suau-Sanchez, Voltes-Dorta, and Rodríguez-Déniz 2016; Lieshout et al. 2016), as well as the economic consequences of airspace inefficiencies (Burghouwt et al. 2016).

In contrast, publications that successfully utilize existing connectivity measurements in a causal research setting (e.g., to explain the spatial pattern in regional development) are rather scarce. We suspect this abundance of literature to be linked to one limitation of current connectivity measurements, which is to only partially consider the cost of air travel in their design. In an end-user perspective, though, we claim that it is the sum of all air travel-related costs that govern individuals' route choice decisions in the short run and might also affect economic development of regions in the long term. Consequently, the objective of this research is to fill this gap and develop a measurement metric that expresses airport connectivity, the degree to which airport's provide access to the global air transport network, in terms of generalized travel costs. That is, we measure the connectivity of an airport by the monetization of factors that yield disutility to travelers starting their air journey at this airport. We further demonstrate the metric's potential for subsequent application. Based on a comprehensive global network of 914 destination airports, we derive and discuss

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seasonal connectivity values for 101 Scandinavian airports for the period between 2004 and 2018.

The remainder of this paper is organized as follows: the next section summarizes the relevant literature; this is followed by a systematic presentation of the metric's methodology; the results for the method's application to Scandinavian airports are then outlined and discussed; and we close with the presentation of policy implicationsand future lines.

2. Literature review

Despite its increasing importance, connectivity remains a somewhat elusive concept as there is no single generally accepted operational definition. While Burghouwt and Redondi (2013) and Zanin and Lillo (2013) provide reviews of applied connectivity measurements, Oxera (2010) and, most recently, ITF (2018) discuss the merits and challenges of different measurement approaches. In general, connectivity metrics can broadly be classified into the following three categories.

First, "quality-weighted metrics" study connectivity by deriving all direct and all reasonable indirect travel paths originating at an airport and valuating their *"relative quality"* (e.g., Veldhuis 1997; Lieshout and Burghouwt 2013). Referring to passengers' disutility from detour and transfers, weights are used to "penalize" the connectivity contributions of indirect travel paths. Constraints on maximum acceptable detours (e.g., Burghouwt and Veldhuis 2006; Lee, Yoo, and Park 2014; Seredyński, Rothlauf, and Grosche 2014) and bounds on tolerable connection times (e.g., Doganis and Dennis 1989; Bootsma 1997; Danesi 2006) are generally enforced. The purpose is to avoid both the generation of travel paths with too short, physically unachievable transfer periods, and the generation of flight paths with extensive transfer times and detours deemed unattractive to demand. On the same grounds, travel paths involving more than one transfer are disregarded from the analysis (e.g., Burghouwt and Redondi 2013; Allroggen, Wittman, and Malina 2015). The extensive set of restrictions applied in quality-weighted metrics induces some notable conceptual and practical challenges. By design, quality-weighted metrics capture connectivity in the "nearest neighborhood" of an airport rather than in a network-wide perspective. Strictly speaking, comparing connectivity scores among different airports, therefore, means comparing airports' integration in different sub-networks. Also, the exclusion of "unreasonable" travel paths based on, for example, some assumed maximum routing factors is for the analysis of geographically remote airports problematic. Such travel paths might still be the only and therefore "best" option for travelers to reach a destination. Hence, their omission can lead to an underestimation of an airport's connectivity as perceived by passengers. Another restraint results from the implied assumption that the marginal connectivity contribution of additional services is constant. In other words, an additional departure yields a fixed connectivity increase, irrespective of the already existing level of departure frequency. Non-linear effects on underlying headways and "schedule delay costs", the costs imposed on traveler by the discrepancy between preferred and scheduled arrival time, are not considered. The same counts for the temporal distance between consecutive departures to the same destination airport. From a passenger perspective, two such flights departing almost simultaneously, for example, might be of a lower value than if the two flights departed with a time lag of some hours.

Second, "shortest path metrics" derive connectivity values based on graph-theoretical concepts. The most relevant type, called the "quickest path length" method (QPL), isolates the specific travel path that minimizes total travel time between an origin and destination airport (e.g., Malighetti, Stefano, and Redondi 2008; Cattaneo et al. 2017). An airport's connectivity value is then operationalized by the average "quickest" travel time from that airport to all its destinations. By design, geographical and network topological information are comprised in such metrics (Zanin and Lillo 2013) and connectivity scores for different airports can be compared based on a consistent set of destination airports. QPL metrics are often criticized as they do not attribute any "connectivity value" to the potentially large set of travel paths that are not the quickest (ITF 2018). In other words, departure frequency is not directly accounted for in QPL methods. Niesse and Grimme (2015) however, recently mitigates the issue and calculate so-called "average shortest travel times", which are sensitive to departure frequency.

Finally, "generalized travel cost metrics" express connectivity as the monetarized disutility occurring to travelers. Generalized travel costs (GTC) embrace the monetized value of in-vehicle and transfer times, airfares, and schedule delay. The lower the average GTC for journeys between an airport and its destinations, the higher the connectivity of the airport. The method's complex modeling approach and comprehensive data requirements (ITF 2018), however, make it a rarely applied methodology. Presumably not designed for the measurement of airport connectivity, the so-called NetCost model introduced by Heemskerk and Veldhuis, 2006a, 2006b, and Veldhuis and Lieshout (2009) is an sole contribution in this class. The model applies the generalized travel cost concept to assess competing direct and indirect travel options in terms of their values as "perceived" by the passenger. At its core, the approach assumes that passengers perceive travel time components yielding from indirect travel paths, such as periods of transfer or detour, as more inconvenient than flight time. These periods are, therefore, panelized relative to (hypothetical) direct travel options. Related publications concern the examination of route choice probabilities (Matsumoto et al. 2009; Lieshout and Matsumoto 2012), the analysis of variations in airline and airport competition over time (Lieshout et al. 2016), and the assessment of welfare implications resulting from air transport system alterations (Burghouwt et al. 2016). It is not evident, however, that "NetCost" models on a sufficiently detailed level to allow for a comparison of airports' connectivity scores across the global air transport network. The method, for example, rather roughly approximates the cost components of schedule delay and airfares. It does also not consider features such as the relative importance of destinations or the preference of passengers for certain arrival times. The conceptual virtue of GTC-based metrics is their ability to integrate the merits of quality-weighted and shortest-path metrics in one measurement. They implicitly "value" service characteristics (departure frequency and fares) as they simultaneously adhere to topological network features (directness, distances, and location). Moreover, the metrics' ability to express connectivity in monetary terms, rather than in some abstract index points, is convenient in assessing a wide spectrum of network characteristics in terms of their welfare implications (ITF 2018). With that, GTC metrics should potentially be the preferred connectivity measurement approach for policymakers and researchers concerned with, for example, the assessment of economic benefits from air transport services. To the best of our knowledge and despite its superior conceptual qualities, no GTC-based metric has been reported that is specifically designed to measure and compare the connectivity of airports on a detailed enough level to facilitate such research. This paper develops such a metric.

3. Methods

3.1. The connectivity metric

We define a digraph $G = (V, A)$, where each node $v \in V$ represents an airport and each arc $a_{(i,j)} \in A$correspondents to a continuously operated scheduled air route between any $v \in V$. $G_{t,s} = (V_{t,s}, A_{t,s})$ thus represents an air transport network in year t and IATA-season s (as defined in IATA (2018)). We denote by $P_{v_{t,s}}$ the set of travel paths originating at $v_{t,s}$ and ending at any destination airport $d \in V_{t,s}$. Thus, $p \in P_{v_{t,s}}$ marks an individual travel path from v to d, via possibly multiple transfer airports $h \in V_{t,s}$. The connectivity measurement proposed in this paper assumes that every $p \in P_{V_{t,s}}$ potentially contributes to the connectivity of airport $v_{t,s}$.

Our method isolates all $p \in P_{v_{t,s}}$ that minimize the generalized travel costs for every 10-min interval of a representative week. Modeling schedule delay and integrating over the course of a week, we create average generalized travel cost values for each origin–destination (O–D) relationship involving $v_{t,s}$ as the origin airport. We express the connectivity of $v_{t,s}$ by the weighted combination of all O-D specific values derived. Assuming travelers to have a preference for arrival time at the final destination and incorporating a weight for potential destination importance, gives us the following connectivity expression:

$$GTCC_{v_{t,s}} = \sum_{\substack{d \in V_{t,s} \\ (d \neq v)}} \omega_d * \sum_{m=1}^{1008} \varphi_m * \min_{p \in P_{V_{t,s}}} (SDE_{p,m} + SDL_{p,m} + TC_p) \tag{1}$$

where TC_p denotes a function of path-specific airfare, monetarized value of in-vehicle time and waiting time at transfer airports, as well as a penalty factor related to possible inconveniences caused by transfers. $SDE_{p,m}$ and $SDL_{p,m}$ denote the costs related to early or late schedule delays of each travel path $p \in P_{v_{t,s}}$ and for each 10-min interval m of the representative week. The weighting parameter φ_m tunes the arrival time preference with respect to m. The parameter ω_d regulates how much an individual O–D relationship contributes to the overall connectivity score of $v_{t,s}$. In line with the underlying concept, we term our metric "generalized travel costs connectivity" (*GTCC*). The following sub-sections outline the parameterization of the metric in different sub-modules.

3.2. Network generation module

For each IATA season, we derive $G_{t,s} = (V_{t,s}, A_{t,s})$ using data sourced from the "SRS-Analyser Flight Schedule Database" (SRS). $G_{t,s}$ represents the network of a typical week in year t and season s. For the definition of the sets $A_{t,s}$ and $V_{t,s}$, the following details apply:

(1) An arc $a_{(i,j)} \in A_{t,s}$ if and only if it is a scheduled, direct air route that originates from any one airport located within predefined geographical bounds (see Section 4.1). Also, $a_{(i,j)} \in A_{t,s}$ if and only if we identify it as a "sustained route" within a specific IATA season $s = \{summer, winter\}$ of year t. The word "sustained" here refers to a minimum degree of route schedule continuance within a season, which we assume is fundamental for passengers to perceive individual air services as part of their choice set and, hence, define their perception of an airport's connectivity. We, therefore, consider only services that have been repeatedly offered at least 20 times (weeks) in a summer season and 15 times in winter. We employ an algorithm that identifies such routes based on individual flight IDs listed in the SRS. The algorithm corrects for minor rescheduling of flights within a season and inconsistent application of flight IDs. Testing against departure statistics for Norwegian airports in 2018, we find our approach can capture approximately 97% of all scheduled departures. We integrate all sustained routes of the same season and design a route schedule representative for a "typical week", ranging from Monday 00:00 to Sunday 24:00.

(2) An airport $v \in V_{t,s}$ if and only if it can be reached with a sustained route $a_{i,j} \in A_{t,s}$. Variations in supply from one season to the next might cause $V_{t,sI} \neq V_{t,sII} \neq \cdots V_{t+n,sII}$, which poses a challenge for the comparison of connectivity scores over time as it might lead to the counterintuitive finding that network size increases but airport connectivity values worsen simultaneously. To circumvent that issue, we map connectivity changes over time in a simplified fashion. We derive what we call a "consistent network", entailing only those airports that were consistently served by scheduled air transport services in the years 2004–2018. We proxy connectivity changes over time based on the development within this network. We assume the resulting bias to be marginal since the "consistent network" represents the overwhelming share of air transport services in each analysis period. For the comparison of connectivity scores in a cross-sectional context, thus, the issue is not relevant, and we can explore the full network of $G_{t,s} = (V_{t,s}, A_{t,s})$.

3.3. Airfare module and block-time estimation

Based on the Norwegian National Air Travel Surveys (Avinor 2017), we derive an airfare dataset with 680,000 observations containing information on path-specific airfares, travel motive, O–D combination, and transfer airports. We disregard incomplete cases from the analysis and exclude observations that report statistics for journeys under Public Service Obligation (PSO), where airfares are subjects to regulatory constraints.

We match this airfare dataset with available supply-side information sourced from the SRS database, such as the scheduled block times for each path segment (i.e., period from leaving the gate to docking the gate), the competitive status on the path segments and whether or not the airline operating a segment is classified as a low-cost airline. For cases where no authentic block times can be identified, we approximate this period based on the spherical distance between two airports and a block-time model. We estimate the model using all non-stop paths in the sample and explain block time by flight distance (Appendix A).

Conducting model selection procedures via repeated exhaustive searches on subsamples (n = 1000) of the dataset, we derive the "best" airfare models for leisure and business travel. Based on the full dataset, we estimate the following two regression formulae that explain path-dependent one-way airfares (see Appendix B for regression table):

$$fare_{b,v,d} = 0.12 * e^{6.92+.003Bt-.13Bt^2*10^{-5}-.49LCC_{dir}+.12Monop_{dir}-.47LCC_{ind}+.12Monop_{ind}+.13TXFR_{one}+.26TXFR_{mult}} \tag{2}$$

$$fare_{l,v,d} = 0.12 * e^{6.45+.004Bt-.18Bt^2*10^{-5}-.24LCC_{direct}+.10Monop_{direct}-.15LCC_{ind}+.07Monop_{ind}} \tag{3}$$

where $fare_{b,v,d}$ ($fare_{l,v,d}$) represents the mean total payable air ticket costs (in 2018 USD; converted from Norwegian Kroners by a factor of 0.12) for a business/leisure-related air journey on a travel path from an origin airport v to a destination airport d (via possibly multiple transfer airports). Bt denotes the aggregated amount of scheduled block time (in min) on the travel path from v to d. LCC_{dir} is a dummy variable indicating that a low-cost carrier (as defined by SRS) operates at least 50% of the overall aggregated block time of a direct travel path (LCC_{ind} for a indirect travel path, correspondingly). The dummy variable $Monop_{dir}$ turns 1 if, on a nonstop path, only one airline/alliance offers services during the same day of the week. $Monop_{ind}$ signals correspondently that, over the course of a day, only one specific airline/alliance offers services on an indirect travel path "out of one hand". Finally, $TXFR_{one}$ and $TXFR_{mult}$ are dummy variables indicating indirect flight paths that involve *one* or *multiple* transfers. The model selection approach mentioned above identifies the latter two dummy variables as consistent features only for the business airfare model. We relate this observation to additional costs that typically only connecting business travelers impose on airlines (e.g., the cost for lounge access or for covering the risk of losing revenue on multiple segments due to flexible ticket category). Consequently, the variables are not included in the leisure airfare model.

We note that our connectivity metric is flexible enough to employ alternative airfare models. Potential users of our methodology might choose to do so in a bid to better fit the prevailing fare structures in other parts of the world or to assess the effects of local airfare characteristics affected by, for example, environmental taxation schemes.

3.4. Path generation module and computation of TC_p

Based on $G_{t,s} = (V_{t,s}, A_{t,s})$, the path generation module identifies for each origin airport the full set of O–D paths ($P_{v_{t,s}}$) and computes their travel costs (TC_p). An algorithm sequentially strings together relevant elements $a_{(i,j)} \in A_{t,s}$ to create $p \in P_{v_{t,s}}$ in the following fashion.

For an origin airport v, all available nonstop routes $a_{(v,j)} \in A_{t,s}$ are identified first, and a set of "reachable" destination airports ($D_{v_{s,t}}$) is initiated. The path-specific travel costs TC_p are derived. Next, all $d \in D_{v_{s,t}}$ are treated as potential transfer airports $h \in V_{t,s}$. The algorithm then connects all $a_{(v,h_1)} \in A_{t,s}$ with all reasonable $a_{(h_1,j)} \in A_{t,s}$, thus creating all one-stop paths originating at v, and computs the corresponding travel costs. The set $D_{v_{s,t}}$ increases in size. Based on the same logic, the algorithm creates all two-stop paths from v next. Additionally, and to reduce computational complexity, it compares all one-stop and two-stop paths to disregard "unreasonable" O–D paths. A path is deemed "unreasonable" if there is an alternative path initiated by the same $a_{(v,h)}$ but which reaches the final destination with lower TC_p. We ensure, however, that no paths are disregarded, which, in a later sequence, might turn out to be preferable because of superior temporal coordination. This sequential process is repeatedly applied until paths to all $d \in V_{t,s}$ are created.

The path generation process has the following constraints:

(i) A path $p \in P_{v_{t,s}}$ if and only if overall travel time satisfies:

$$ArrT_{d_{t,s}} - DepT_{v_{t,s}} \le \begin{cases} 36h & , p \;\; is \;\; domestic \\ 72h & , p \;\; is \;\; intenational \end{cases} \tag{4}$$

That is, for paths where the origin and destination airports are located in the same country not more than 36 h, for all other cases 72 h overall travel times are allowed. Overall travel time is the time between scheduled departure at an origin airport ($DepT_{v_{t,s}}$) and the scheduled arrival time at a final destination airport ($ArrT_{d_{t,s}}$). The constraint is set to ensure a balance between reducing computational burden and ensuring network consistency. With respect to the latter, we found that creating paths between geographically distant airports at times require such extensive travel time constraints.

(ii) A path $p \in P_{v_{t,s}}$ if and only if each necessary transfer satisfies:

$$DepT_{h_{t,s}} - ArrT_{h_{t,s}} \ge \begin{cases} MinCT_1, \; z_{a_{(i,h)}} \equiv z_{a_{(h,j)}} \\ MinCT_2, \; z_{a_{(i,h)}} \in Z_{a_{(h,j)}} \vee z_{a_{(h,j)}} \in Z_{a_{(i,h)}} \\ MinCT_3, \;\; z_{a_{(i,h)}} \notin Z_{a_{(h,j)}} \wedge z_{a_{(h,j)}} \notin Z_{e_{(i,h)}} \end{cases} \tag{5}$$

where $z_{a_{(i,h)}}$ denotes an airline serving an arrival route and $z_{a_{(h,j)}}$ is an airline operating a departure route at transfer airport h. $Z_{a_{(h,j)}}$is a set containing all airlines being identified as alliance members or code-sharing partners of airline $z_{a_{(i,h)}}$ ($Z_{a_{(i,h)}}$ and $z_{a_{(h,j)}}$, respectively). In other words, we define that the period between the scheduled arrival time of a route at a transfer airport ($ArrT_{h_{t,s}}$) and the scheduled departure time of a route from the same airport ($DepT_{h_{t,s}}$) must not be shorter than a specified minimum connection time ($MinCT$).

In Eq. (5), we distinguish transfers between routes served by the same airline/subsidiaries ($MinCT_1$), by different airlines of the same alliances/code-sharing partners ($MinCT_2$), and by airlines without cooperation agreement ($MinCT_3$). Additionally, we distinguish $MinCT$ with regard to six route type combinations (e.g., transfer from domestic to intercontinental flight). In line with recommendations for transfers at Scandinavian hub airports as provided in SAS (2018), we assume uniform values for all airports as shown in Table 1.

Table 1
Minimum connection times in minutes.

Type of cooperation	Route type combination					
	$a_D - a_D$	$a_D - a_E$	$a_E - a_D$	$a_E - a_E$	$a_D - a_I$	$a_E - a_I$
$MinCT_1$	25	35	40	30	45	45
$MinCT_2$	40	50	55	45	60	60
$MinCT_3$	100	110	115	105	120	120

Note: 'a_D' – domestic route; 'a_I' – route with a destination outside Europe; 'a_E' – all other.

For purely domestic connections at airports identified in EC (2018) as "PSO airports", $MinCT_1$ is reduced to 10 min. This relaxation is necessary to correctly reflect operations on multiple PSO-routes, where aircraft turnaround times can be very short. We further consider "self-help hubbing" (Malighetti et al. 2008), the phenomena of passengers buying separate tickets (of possibly different airlines) to build their own connection on indirect air journeys, as a feasible alternative. We cover the more severe consequences of missing a connecting flight for "self-hubbers" (Fichert and Klophaus 2016), as well as the additional time needed for baggage claim and re-check-in by an additional markup of 60 min in $MinCT_3$ (subject to sensitivity analysis in Section 4.3). Thus, our method trades passengers' disutility from higher $MinCT$ for "self-hubbing" with the potential gains from using low-cost airlines or from higher directness of the "self-help-hubbing path". We see this high degree of differentiation in minimum connection times as more realistic than provided in earlier analyses, which either apply one undifferentiated value for all types of transfers (e.g., Veldhuis 1997) or distinguish for route type combinations alone (e.g., Lee, Yoo, and Park 2014). In fact, our approach allows the form of contractual cooperation between airlines at a transfer airport h to contribute to the connectivity of an airport v, if it's travel paths connect via h.

For computing travel costs TC_p, the following assumptions are used:

- In line with the segmented air transport demand in Norway (Thune-Larsen and Farstad 2016), we estimate path-specific airfares by weighting Eqs. (2) and (3) in a ratio of 4 to 6. We assume that this ratio is representative also for other Scandinavian airports.
- After consolidation for different travel purposes (Thune-Larsen and Farstad 2016), periods of in-vehicle time (IvT) are valued by 0.72$/minute (Killi, Halse, and Flügel 2010).
- Periods of transfer time are valued equal IvT. We note that other connectivity metrics typically value transfer time in multiples of IvT, reasoning that the traveler "perceive" transfer time as more inconvenient than IvT (e.g., Matsumoto et al. 2009). Veldhuis (1997), for example, applies a multiplier of three to reflect the risks of missing connecting flights and of losing luggage during transfers. Our method does not follow this practice. We argue that the aim of establishing minimum connection times ($MinCT$) at airports is to mitigate the risk of missing connection flights. Penalizing $MinCT$ periods minute by minute would, therefore, lead to "double counting" this disutility. Second, we claim that waiting times at airports can yield higher utility levels than in-vehicle times. People might find airport facilities much more convenient for shopping and work-related activities than the constrained space inside an aircraft cabin. We acknowledge, though, that there is always some degree of inconvenience. Adapted from Ramjerdi et al. (2010), we apply a transfer penalty period equal to 10 min IvT for each transfer on a path. Applying different monetary valuations of IvT for business and leisure travel motives scale the penalty factor for travel purposes.

Note that all aforementioned assumptions are designed to best suit the analysis of Section 4. The application of the metric to airports outside of Scandinavia might require adjustments (e.g., valuation of time).

3.5. Rooftop module

Passengers have to plan and conduct their journeys according to existing flight schedules. A possible misalignment between a passenger's preferred and the scheduled arrival time at a destination poses a cost to the traveler, called the "schedule delay cost" (Small 1982). The magnitude of schedule delay cost 'early' (SDE) or 'late' (SDL) is thereby not only dependent on the sheer number of arrival frequencies within a certain period of time, but also on the temporal structure of the arrival schedules. That is to say, the temporal distance between consecutive arrivals drives schedule delay. An analysis tool to consider frequency and the effects of this temporal structure in timetables is the so-called "rooftop model" (Douglas et al. 2011; Kroes and Daly 2018).

We exemplify the rooftop approach on an O–D combination for which the path generation process (Section 3.4) hypothetically identified five existing paths (Fig. 1). We map the five travel paths (grey vertical line) with respect to their scheduled arrival time at d (x-axis) and their corresponding transportation costs TC_p (y-axis). For a traveler for whom the preferred arrival time is equal to their scheduled arrival time, the generalized travel costs are equal to TC_p. For a traveler whose arrival time preference differs from the scheduled arrival time, a fixed per-minute schedule delay cost is added (blue sloping lines). Travelers are assumed to behave cost-rationally and to choose the distinct travel path that minimizes GTC with respect to the preferred arrival time. Consequently, a graph representing the minimum possible GTC for each arrival time interval can be deduced (dashed black line). This graph can then be

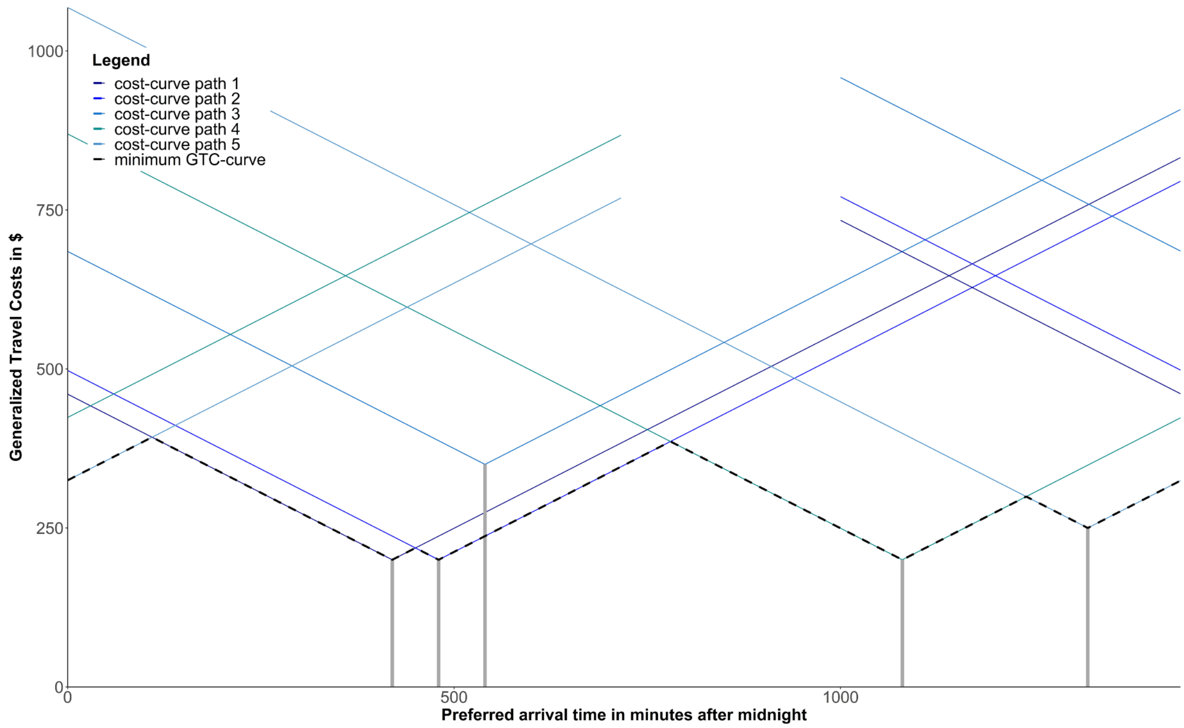

Fig. 1. Rooftop model - graphical representation. Note: For practical purposes, we limit the example to cover only one day.

used to represent the minimum *average GTC* for an air trip from origin airport v to destination airport d.

Fig. 1 reveals three features of rooftop modeling beneficiary for our connectivity metric. First, the temporal "closeness" of paths 1 and 2 reduces their individual impacts on overall schedule delay costs. Second, due to its high TC_p, path 3 does not define the "minimum GTC curve". Hence, path 3 does not contribute to the connectivity between v and destination airport d. The relatively "expensive" path 5, on the other hand, contributes to the connectivity of v. Its high TC_p are offset by the positive impact that its relative temporal "isolation" has on schedule delay costs.

In line with the aforementioned example, we compute "minimum GTC curves" for all relevant O–D combinations based on 10-min intervals (local time) of the "typical week". We follow Ramjerdi et al. (2010) and "value" *SDL* and *SDE* equal to 0.4 times *IvT* (subject to sensitivity analysis in Section 4.3). Compared to what Lijesen (2006) reports, these values can be regarded as conservative.

3.6. Arrival time preference weight φ_m

Assuming traveler to have a preference for arriving at their final destination airport at a specific time of day, we study hourly passenger statistics of three short-haul, *high-frequency* city-pairs in Norway for the year 2017. On such routes, we presume passengers can travel on the specific flight that minimizes their schedule delay costs (all else equal) and hence, the statistics reveal their preferences with respect to arrival time. We aggregate all observations in the dataset and derive a representative 24-h arrival profile. In line with the preference pattern identified for air travel in Canada and the US (Koppelman et al. 2008; Brey and Walker, 2011), we find that mid-morning and late-afternoon arrivals are the most preferable. We follow the approach in Brey and Walker (2011) and model the observed "two-peak formation" by a probability density function $p(x)$ based on a mixture of 'K' normal distributions as follows:

$$p(x) = \sum_{k=1}^{K} \lambda_k (n(\mu_k, \sigma_k)) \tag{6}$$

where $n(\mu_k, \sigma_k)$ is a Gaussian probability density function with mean μ_k and standard deviation σ_k. The parameter λ_k denotes the mixture parameter for the distribution. We model the distribution with $K = 3$ (i.e., the mixture of three normal distributions). The resulting parameter values (Table 2) allow us to derive φ_m for each 10-min interval m of the representative week. We apply φ_m to the identified minimum GTC curves and weight them for assumed arrival time preference. This entails that periods of high arrival time preference (e.g., mid-morning) contribute relatively more to the final connectivity score of an airport than periods of low arrival time preference (e.g., midnight). Note that this procedure affects all cost components of a GTC curve, including the schedule delay costs.

Table 2
Mixture density function, parameter values − 24-hour time interval.

Parameters	Normal Distribution		
	$k = 1$	$k = 2$	$k = 3$
λ_k	0.245	0.179	0.575
μ_k	8.963	11.938	18.636
σ_k	0.996	1.369	2.335

Note: Based on aggregated hourly passenger arrivals at Oslo (OSL) in 2017 for routes from Trondheim, Stavanger and Bergen.

3.7. Destination importance weight ω_d

We argue that airports, in their role as access points to the air transport network, contribute to their hinterlands' economic prospects, by lowering the costs of interactions with distant regions/airports. The better integrated an airport v is within the network, the lower the interaction costs for its users and thus, the better the prospects for its hinterland. However, it seems unrealistic to assume that all destination region/airports equally affect the prospects at v.

To discriminate for different levels of interaction opportunities between regions (Hansen 1959), we introduce a destination importance weight ω_d. As a point of departure, we follow the general layout of the market potential model proposed by Harris (1954). He claims that the (economic) potential of a location (in our case the hinterland of airport v) is proportional to the "size" of a market (in our case the hinterland of a destination airport d) and inversely proportional to the cost of transportation between v and d. We adjust this formulation and derive the following:

$$\theta_{(v,d)} = \partial_d / GTC_{(v,d)} \tag{7}$$

In Eq. (7), $\theta_{(v,d)}$ denotes the interaction potential of v with respect to d, which stems from the exiting transportation link between v and d. It is proportional to ∂_d, the economic output in the hinterland of destination airport d, and inversely proportional to $GTC_{(v,d)}$, the average generalized travel costs for journeys between airport v and airport d.

To proxy the economic output of an airport's hinterland, we consult the database GEcon4.0 (2011). We source statistics on "gross value added" for some 27,000 global grid cells of 1-degree latitude by 1-degree longitude for 2005. We extrapolate for future years with national growth rates sourced from WorldBank (2018). Correcting for differences in grid cell size with respect to latitude and assuming that economic output is equally distributed within a grid cell, we approximate the gross value added within a 75-km radius around each destination airport. We acknowledge that a 75-km catchment area is rather small compared to previous literature (e.g., Matisziw and Grubesic 2010). However, the risk of double-counting economic output escalates with the definition of increasing catchment area size. Based on a pragmatic comparison of Europe's landmass and the number of existing European airports in 2018, we find a 75-km definition acceptable. For cases where catchment areas of airports overlap, we employ an algorithm that distributes the economic output of the "overlapped area" among the involved airports.

We then go on to determine the relative importance of airport d for the connectivity of v and derive destination importance weight ω_d by:

$$\omega_d = \theta_{(v,d)} \Bigg/ \sum_{\substack{d \in V_{s,t} \\ (d \neq v)}} \theta_{(v,d)} \tag{8}$$

Note that, in Eq. (7), ∂_d is dependent only on the characteristics of the hinterland of d at a specific moment in time, hence independent of features at v. This term remains unchanged, provided that the interaction potential is calculated from the perspective of different origin airports. But the denominator in Eq. (7) incorporates effects of both the geographical positions of v and d in the network and the service features for air travels between v and d. This term is, therefore, distinct for each O–D specification and changes with alteration in the network. In the hypothesis that $GTC_{(v,d)}$ declines from one year to the next, $\theta_{(v,d)}$ increases. This is because the "economic mass" of d is pulled toward v. The overall importance of d for the connectivity computation of airport v increases. The maximum "closeness" between v and d is reached in the hypothetical case that there exists an infinite number of direct frequencies between the two airports. The denominator in Eq. (7) then contains only those "unavoidable" costs that result from the geographical position of v relative to the location of d. The corresponding O–D-specific importance weight ω_d reaches its maximum (all else equal).

4. Application

4.1. Network definition

We apply the metric developed in this paper and calculate the connectivity scores for 101 Scandinavian airports and for each individual IATA-season between 2004 and 2018[1]. For this setting, we define the air transport network $G_{t,s}$ to consist of all sustained routes $a_{(i,j)} \in A_{t,s}$ departing from any airport located within Europe (including the four westernmost Federal District of Russia) and all $v \in V_{t,s}$ that are linked by any $a_{(i,j)} \in A_{t,s}$. Therefore, $V_{t,s}$ contains both European and non-European airports. Even though it seems highly admirable to include the entire global air transport network in the analysis, this network demarcation is necessary to keep computational complexity within manageable levels. Fig. 2 illustrates the geographical extent of the network analyzed in this case. For the "typical week" of the winter season in 2018 for example, the network contains some 914 destination airports, while some 139,000 "sustained" routes are employed in the analysis.

4.2. Results

4.2.1. Connectivity scores – I/2018

In Fig. 3(a), we show the overall GTCC values for Scandinavian airports in the winter of 2018[2]. Note that all GTCC values are expressed in 2018 Dollar. Several features stand out.

First, connectivity values among the airports differ noticeably ($\mu = 1105;\ \sigma = 467$). The "best" connected airport in the sample is the airport of Copenhagen (CPH), which reaches a weighted GTCC value of 582. This score suggests that a passenger starting her/his air journey at CPH faces a generalized travel cost of on average \$582 (i.e., the weighted average across all global network destinations shown in Fig. 2). Copenhagen's connectivity value differs from the scores of the second-best airports by approximately 15%, indicating a substantial "connectivity advantage". In general, the national hub airports of Copenhagen (CPH), Stockholm (ARN), Oslo (OSL), and Helsinki (HEL) are the "best" connected airports in their respective country.

On the opposite end, the GTCC values for the trailing airports are about 2.5-times as high, indicating a considerably lower connectivity level (see Appendix C for further details). Yet, we find the overall range of scores to be much more homogenous than the results of a computation based on existing quality-weighted connectivity measures. In Wittman et al. (2016), for example, the connectivity between the best connected and least connected airport in Norway alone differs by a factor of 500. We relate this discrepancy to the fact that our method can assess an airport's degree of global, instead of local network integration. In contrast, comparing our results with those of a "shortest path-based" study presents the opposite finding. While Malighetti et al. (2008) identify the connectivity of CPH, ARN, and OSL to differ only by maximal 4% for the year 2007, we measure this difference to be around 17% during the same period. We relate this observation to the QPL-metrics characteristics to build connectivity scores exclusively based on one, best "shortest path" for every O–D relation. The effects of varying service levels across a week, for example, cannot be factored in.

We further notice that connectivity scores in Norway and Finland seem to decrease with the more northerly location of the airport. We relate this observation to two factors. First, population density in Scandinavia generally decreases the further north one goes. Assuming that air transport service levels (e.g., departure frequency) follow this pattern, connectivity scores derived with our method will intuitively decrease with increasing latitude for the case of Scandinavia. Second, we assume that an airport's geographical location relative to the locations of all destination airports is an important determinant of its connectivity score. Air journeys to central Europe originating at an airport in northern Norway, for example, will on average require longer flight distances to overcome than trips starting at airports in southern Norway. Generalized travel cost based connectivity scores of remote airports thus contain a location-specific connectivity "penalty".

To assess the magnitude of this locational disadvantage for our sample, we perform a computational experiment in which we simulate that each airport is linked to all $v \in V_{2018,I}$ by direct air services. We further assume that all links are operated by competing low-cost airlines and with infinite departure frequencies. Computing the spherical distance between the airport pairs and applying the block time model (Appendix A), we thus calculate the GTCC score for the hypothetical case that travelers can completely avoid disutility from schedule delay, indirectness of travel paths, and non-optimal service levels. The resulting score can be interpreted as the "best theoretically possible" connectivity values an airport can achieve, given its geographical location within the network at hand.

Using these scores, a linear regression model yields that additional 100 miles in latitude/longitude come with a "locational penalty" equivalent to \$12 (\$6). The most northerly airport in the sample (LYR), for example, has a "locational disadvantage" equal to \$200 compared to the southernmost airport (SGD). That is, even if comparable levels of air transport services were offered at both airports, SGD would still achieve considerably better connectivity scores. We correct the genuine connectivity scores for an airport's locational disadvantage in Fig. 3(b) and realize that the low connectivity values of the northernmost airports in Norway, for example, cannot exclusively be attributed to the geographical remoteness of the airports. The consequences of low-frequency services and indirect routings take effect.

For Sweden and Denmark, no clear-cut pattern in terms of geographical latitude can be identified. Multiple airports in the south of both countries and close to major settlement structures score rather poorly. We link this finding to the generally better landside accessibility of airports in these countries, their proximity to each other, and the resulting spatial concentration of air services.

Elaborating further on the general distribution of connectivity scores, Fig. 4 plots airport-specific connectivity values grouped by country. To the left, the distribution of scores in the "global perspective" shows that Danish airports on average achieve considerably

[1] The period was constrained by accessibility of sufficient flight schedule data on the SRS Analyzer. To avoid bias from starting the analysis in a period subject to severe shocks (e.g. 9/11, SARS), we examined several supply statistics and found the year 2004 to be an acceptable point in time to start the analysis with.

[2] The winter season of 2018 is used as a reference throughout this section to facilitate a comparison of scores over time, unbiased from seasonal effects. Due to the high correlation between summer and winter scores, the findings presented in this section, in general, are valid for the summer season of 2018. The interested reader might consult Appendix C for further details on airport-specific winter and summer scores.

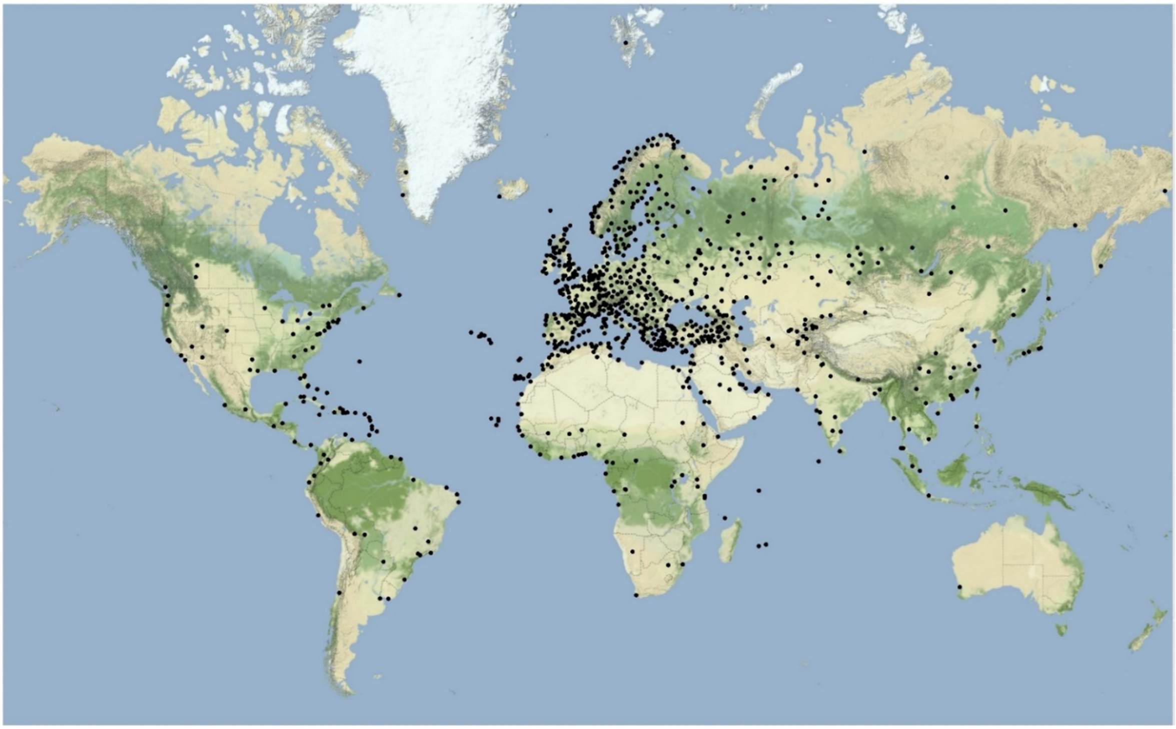

Fig. 2. Network size – I/2018.

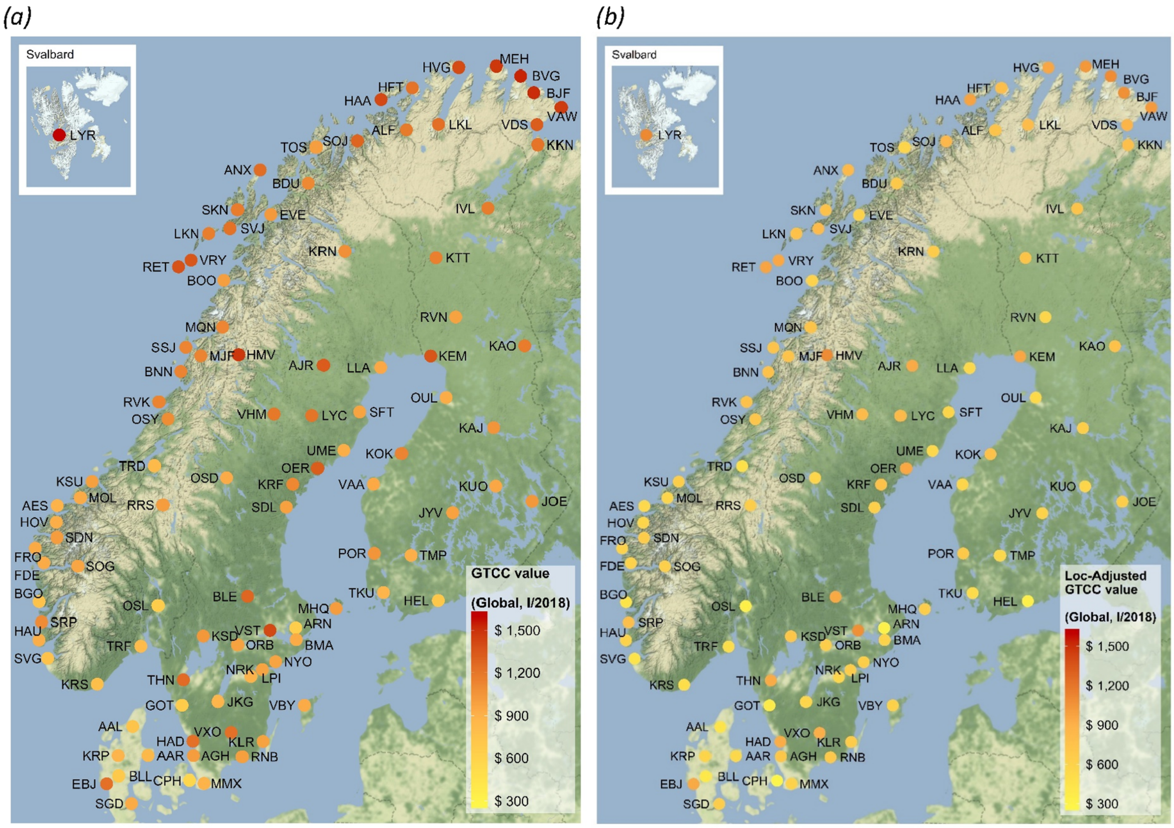

Fig. 3. Global connectivity scores I/2018. (a) absolute values and (b) adjusted for geographical location. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

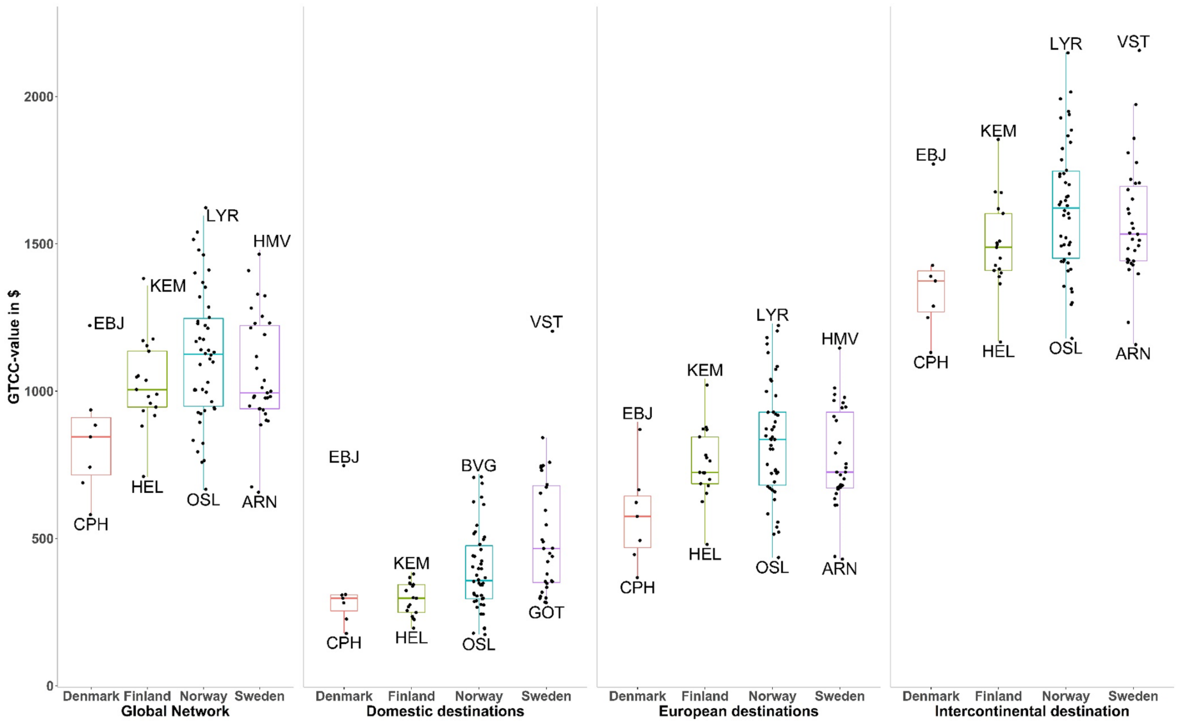

Fig. 4. Connectivity scores I/2018 - distribution per country and sub-network. Note: Scatter plots are 'jittered' to increase perceptibility; lateral distance between dots is random.

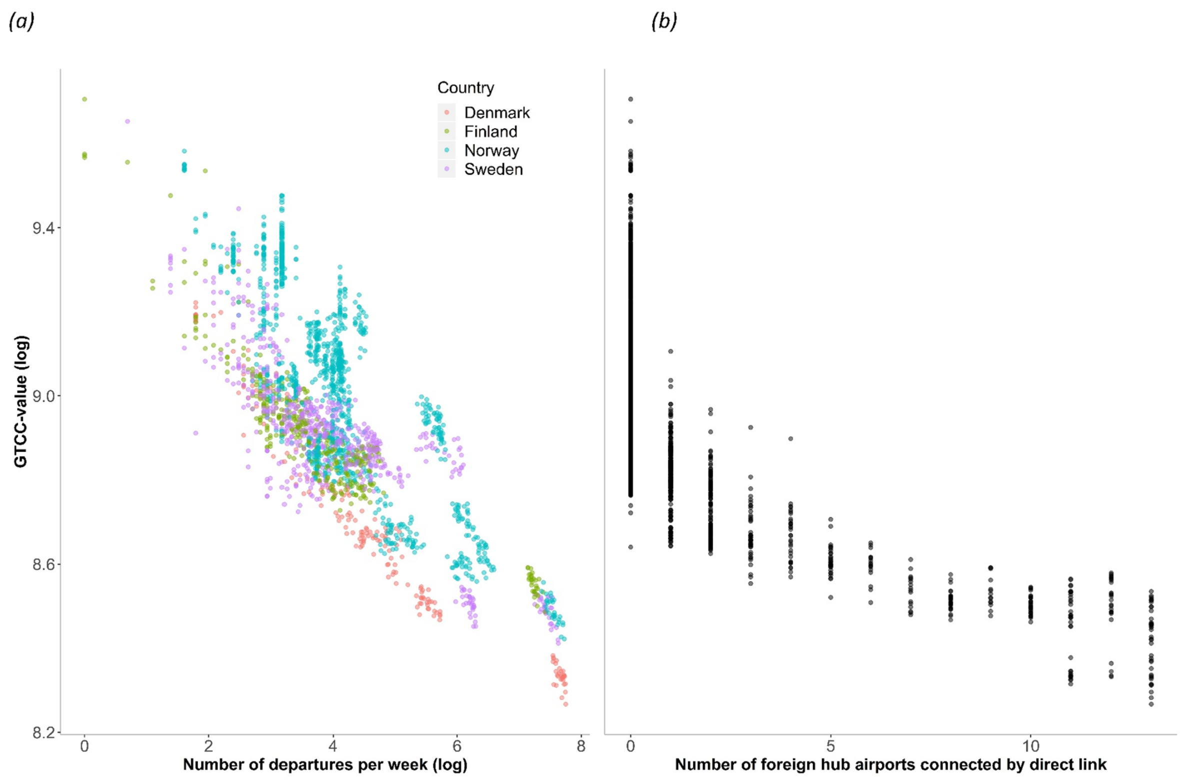

Fig. 5. Global connectivity scores 2004–2018 (log). (a) vs. the number of weekly departures (log) and (b) vs. the number of foreign hubs linked to by nonstop route. Note: The graphs utilizes panel data (2004–2018) of the consistent network dataset; "foreign hub airports" defined as {OSL, ARN, CPH, HEL, CDG, AMS, MUC, FRA, MAD, LGW, LHR, DXB, DOH, IST}. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

better values than airports in the other Scandinavian countries. In part, this is related to a more favorable geographical location in an overall network perspective.

4.2.2. Sub-network perspective and cost components

We construct three distinct sub-networks (Domestic, Europe, and Intercontinental) and calculate connectivity scores for each airport, assuming that only travel paths to destinations in the sub-networks are relevant. Even though we believe the “global” scores to be the most appropriate representation of an airport's connectivity, the rationale behind a separate analysis for each of the three sub-networks is to explore the full informative potential of our method. The “global” score of an airport reflects the degree of accessibility that the airport provides to its customers in a global network perspective. If literally interpreted in terms of generalized travel costs, these global scores might be less informative for policymakers that are concerned with, for example, aspects of domestic transport planning. It is because generalized travel costs on domestic flights are, conditioned by shorter flight distances, generally lower than those on intercontinental flights. Hence, global connectivity scores do overstate the level of generalized travel costs that passengers typically encounter on domestic air travels. Analyzing the three sub-networks separately allows us to derive connectivity scores in a more representative way for different destination categories and to provide insights into how individual airports perform in relation to their competitors in those categories. A potential user of our method might choose, dependent on the specific research objective at hand, to conduct an analysis based on one of the sub-network perspectives.

For the ‘Domestic sub-network’ for example, we analyze only travel paths that link airports of the same country. We find that average *domestic* GTCC values are generally lower than the global ones (Fig. 4) and note that Finnish airports are, on average, better connected with each other than Swedish and Norwegian airports. Also, Finnish airports appear to achieve “relatively” homogeneous connectivity scores. In the *European* and the *intercontinental* network perspective, the distributions among Finnish, Norwegian, and Swedish airports appear to be rather equal. As for the global perspective, Danish airports seem to score comparably well in all three sub-networks.

We also observe that the difference in connectivity scores between the best- and worst-performing airports of each country appear to increase from the domestic to the intercontinental segment. We relate this observation to the fact that the airports with the poorest scores generally provide low departure frequencies (Fig. 5(a)). In a domestic travel context, low frequencies translate mainly into high schedule delay costs. For international journeys, low frequencies at origin airports might additionally lead to pure temporal co-ordination at transfer points and hence relatively higher generalized travel costs. Moreover, we find that GTCC scores are negatively correlated with the number of foreign hub airports an airport is connected to by a direct link (Fig. 5(b)). The existence of such links potentially generates multiple indirect travel paths that are more attractive to a traveler than alternatives via a country’s domestic hub. The advantage of being linked to foreign hubs though has more of an effect on international than for domestic journeys.

To elaborate further on the details behind an airport's connectivity score, we analyze to which extent each of the generalized cost components contributes to the total connectivity value (see Appendix D for individual airport results). Based on a selection of high and low connectivity airports in Table 3, we find that costs related to in-vehicle time and airfare are generally the most important individual cost components across the spectrum of airports. We see a tendency that their relative contributions decrease with increasing connectivity value. In contrast, the relative importance of costs related to waiting time in transfer and the number of transfers increase with rising connectivity scores. The counteracting tendencies reflect that travel paths originating at purely connected airports often involve multiple transfers, whereas high directness and good temporal coordination from hub-airports drive the relative importance of transfer related costs down[3].

Table 3
Connectivity scores I/2018 – Cost components.

			$GTCC_{2018/I}$	Cost components in USD					Cost components in %				
Airport name	IATA code	Country	Global	SD	IvT	Fare	TT	TP	SD	IvT	Fare	TT	TP
Copenhagen	CPH	Denmark	582	66	207	252	53	4	11.3	35.5	43.2	9.1	0.8
Stockholm	ARN	Sweden	657	69	238	276	68	5	10.5	36.3	42.1	10.3	0.8
Oslo	OSL	Norway	664	65	240	278	75	6	9.8	36.1	41.9	11.3	0.9
(…)													
Ängelholm	AGH	Sweden	1011	113	313	372	200	14	11.1	30.9	36.8	19.8	1.4
(…)													
Båtsfjord	BJF	Norway	1513	159	438	507	373	36	10.5	29.0	33.5	24.7	2.4
Berlevåg	BVG	Norway	1538	161	440	505	398	35	10.5	28.6	32.8	25.9	2.2
Svalbard	LYR	Norway	1594	236	442	471	427	18	14.8	27.8	29.6	26.8	1.1

Note: Schedule delay (SD), in-vehicle time (IvT), airfare (Fare), transfer time (TT), transfer penalty (TP).

If compared in absolute terms, we find that weakly connected airports underperform across all cost components. Here multiple factors take effect. Low departure frequencies, for example, drive up scheduled delay costs, whereas the lack of direct flights to multiple destinations increases costs for on-board time and the lower levels of competition at smaller airports raise average airfares.

[3] We note that these findings are sensitive to the specific assumptions made in Section 3.

Table 4
Connectivity scores I/2018 – Scandinavian vs. six major European hub airports.

			$GTCC_{2018/I}$	$GTCC_{2018/I}$(segmented)		
Airport name	IATA code	Country	Global	Domestic	European	Intercont.
Amsterdam	AMS	Netherlands	419	437*	265	975
Frankfurt	FRA	Germany	439	211	311	972
Paris	CDG	France	454	324	297	962
Munich	MUC	Germany	454	206	324	1062
London	LHR	UK	492	319	341	938
Istanbul	IST**	Turkey	725	277	499	1135
Copenhagen	CPH	Denmark	582	179	367	1131
Stockholm	ARN	Sweden	657	284	432	1160
Oslo	OSL	Norway	664	175	435	1179
Helsinki	HEL	Finland	708	197	481	1169

Note: *Few direct domestic services exist; 'best' travel paths are derived connecting via foreign transfer airports; ** Istanbul Atatürk airport (IATA-code 2018)

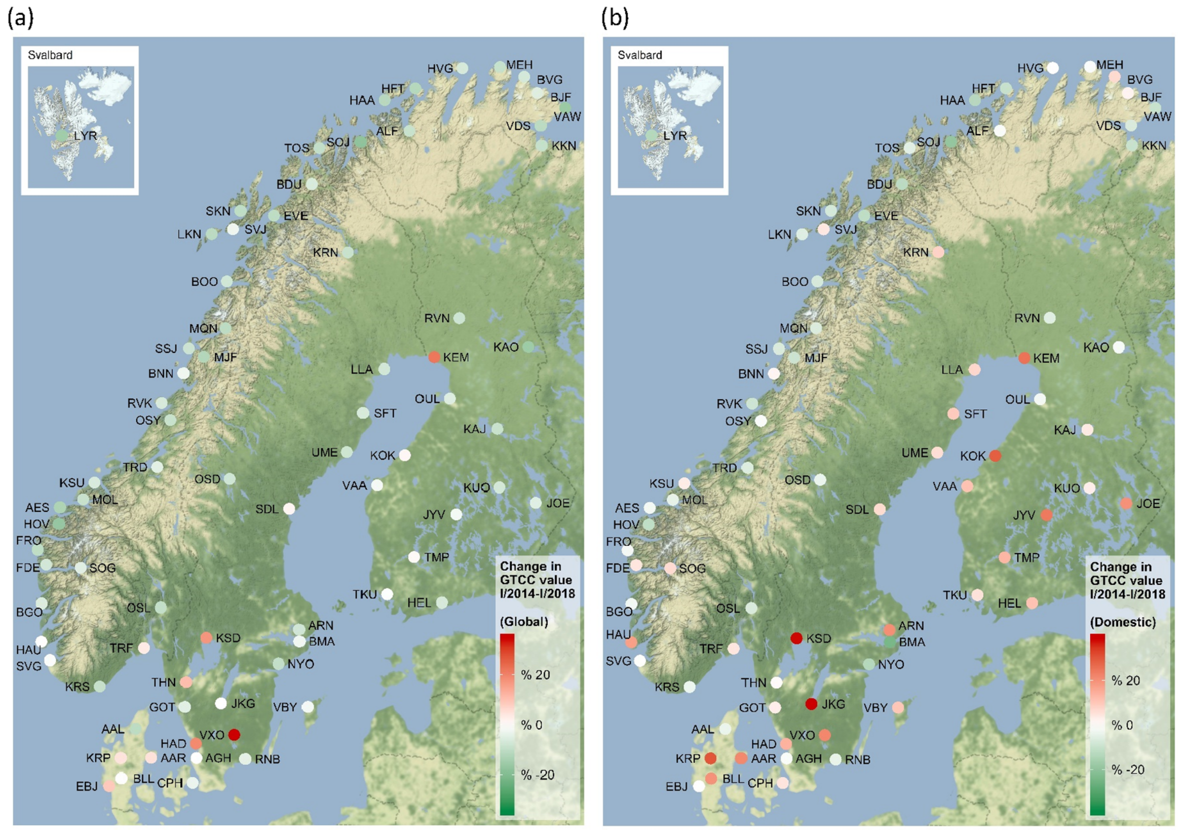

Fig. 6. Change in connectivity scores I/2018 relative to I/2004. (a) Global network and (b) Domestic network definition. Note: Green color indicates an improvement, red color a decline in an airport's connectivity. Airport Stockholm-Västerås (VST; +53%/+173%) omitted to improve scalability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2.3. Hub-perspective

We notice across all destination segments (Fig. 4) that the national hub airports generally achieve the best connectivity values within a country, and that their edge is most pronounced for journeys to European and intercontinental destinations. With a view to assessing the connectivity values of the Scandinavian hub airports more comprehensively, Table 4 contrasts their scores with those of the six European hub airports with the most departure flights in 2018. In this respect, the connectivity of the Scandinavian hub airports is relatively low. Generalized travel costs for air journeys starting, for example, at Amsterdam airport, are on average 40% cheaper than from Helsinki. Scandinavian hub airports are most "competitive" in a domestic network context. We associate this with the high importance of domestic air travel in Scandinavia. In other countries, though, modes of surface transportation are more suitable for domestic travel. In addition, the aforementioned locational "penalty" takes less effect in the domestic than in the international network context.

4.2.4. Connectivity development from 2004 to 2018

Analyzing the "consistent network" (see Section 3.2), we assess the development in connectivity scores between 2004 and 2018. Comparing the global scores per season for both years, we find predominantly an improvement in connectivity values by approximately 6.5% for the winter and 4.8% for the summer season (both median observations). In Fig. 6(a), a few notable exceptions from this trend can be detected. We find mainly within the area of southern Sweden and Denmark several airports that have experienced a decline in connectivity. We interpret this divergence as an indication of an increased concentration of services at larger airports in this region.

In the domestic context, we identify a more diverse picture (Fig. 6(b)). Between 2004 and 2018, domestic connectivity has mostly improved at Norwegian airports by approximately 6% (summer 2.5%), whereas the connectivity at Danish, Swedish, and Finnish airports has, on average, declined (winter: 12%; 7%; 11%, summer: 13%; 13%; 11%). Since our method employs a time-invariant airfare formula and airport location is fixed by design, the development shown can essentially be attributed to changes in service levels at the airports and the resulting effects on the temporal network coordination within the domestic networks.

In Fig. 7, we map the development of the global connectivity scores for the national hub airports between 2004 and 2018 and contrast these with the development of the average connectivity scores of all other airports of a country.

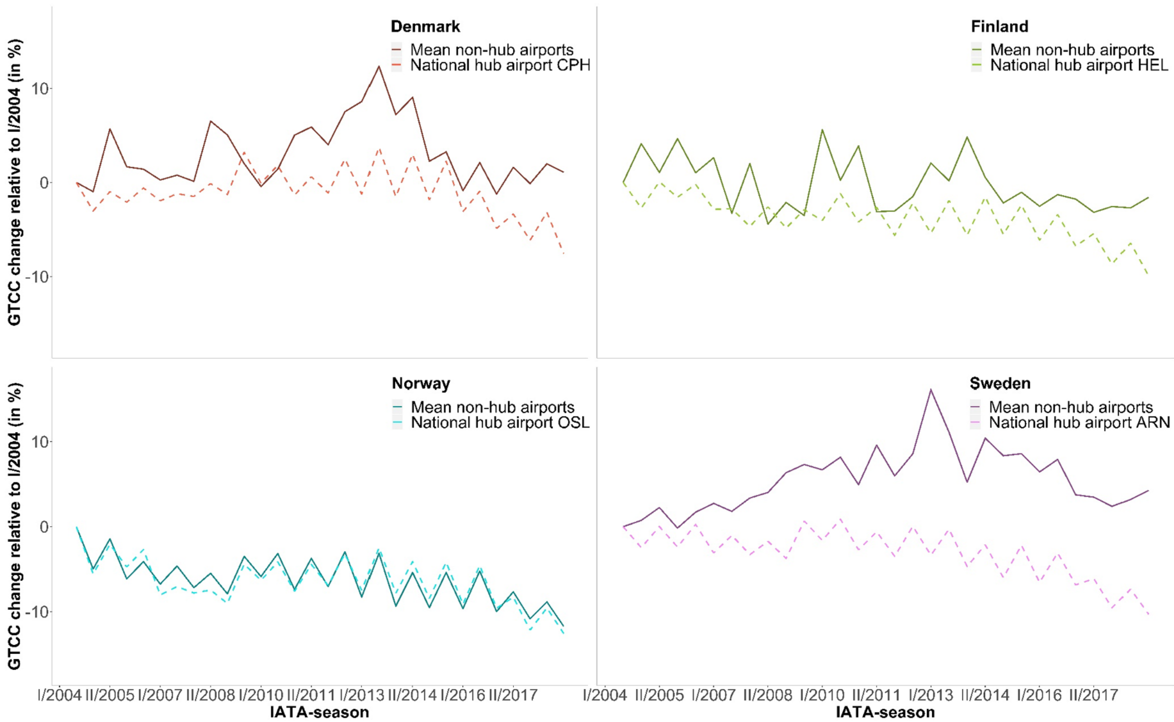

Fig. 7. Development of connectivity scores I/2004-II/2018.

We find that all national hub-airports have improved their connectivity. Averaging the development for summer and winter seasons, the accumulated gains range between 4% and 8.5%. Copenhagen has made the least progress and seems to have achieved improvements only in the most recent years, whereas Helsinki and Oslo gained an edge in the earlier years of 2008 and 2009. In absolute values, however, Copenhagen has consistently achieved substantially better connectivity values than the other hubs.

Further, we find indications for an increasing spatial concentration of connectivity within national networks, as shown by the spread in the development between the "mean" and the "hub" scores. In other words, the connectivity growth at hub airports has generally outperformed the development at non-hub airports. Only in case of Norway, the development within the rest of the national airport system has kept pace with the scores of the national hub airport (for detailed numbers, see Appendix C).

Finally, the graphs suggest that connectivity scores might follow a distinct seasonal pattern. We calculate winter-to-summer ratios for all sample airports and all seasons and find that hub-airports tend to have on average 3–4% better connectivity during summer than winter seasons. For non-hub airports, we identify winter-to-summer ratios between 1.21 and 0.83, with airports on the lower bound typically being located in Finland and Sweden and serving winter tourism destinations.

4.3. Limitations and sensitivity analysis

The method proposed in this article draws on existing literature for parametrization. We note that the literature is often inconclusive and suggests a rather wide range of values to apply. To assess the sensitivity of our results to alterations in some of our key assumptions, we conduct a sensitivity analysis and recalculate global GTCC scores for the five airports with the lowest and the five

Table 5
Sensitivity analysis.

	GTCC scores (% – change)								
Airport category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
high connectivity ($\bar{GTCC}_{2018/I}$=653)	3.4	16.9	5.7	0.1	0.0	−2.0	3.3	9.5	2.5
low connectivity ($\bar{GTCC}_{2018/I}$=1520)	2.9	14.2	17.2	5.1	2.2	−2.8	12.6	44.9	8.6

Note: Positive values imply a reduction in connectivity and negative changes an improvement.

airports with the highest connectivity values (see Appendix C). We derive the mean GTCC values for both airport groups and show deviations with respect to the original GTCC results in Table 5.

In Columns (1) and (2), we increase the valuation of *Ivt* by 10% and 50%, respectively, and in Column (3), the valuation of schedule delay by 50% (i.e., 0.8**Ivt*). Next, sensitivity to adjustments in *MinCt* is tested. First, we increase *MinCt* flat by 30 min no matter the type of airline cooperation or route type combination (Column (4)). In Columns (5) and (6), we alter *MinCt* only for "self-hubbing" connections by +30 and −30 min. Finally and to reflect the heterogeneous body of literature on the valuation of periods in transfer, we value such periods with 1.5- and 3-times *Ivt* in Columns (7) and (8). We then analyze the effects of applying a fixed transfer penalty equal to 1-h *Ivt* for each transfer on a travel path, no matter the duration of the transfer period(s) (Column (9)).

In general, the results indicate that all alterations influence the GTCC scores in a comprehensible fashion. The changes in assumptions that affect specific types of airports over-proportionally are most critical for our method. We explicitly identify modifications in the valuation of transfer periods and schedule delay to increase heterogeneity in our results. Consequently, additional research aiming at the valuation of such periods might help to reduce the level of uncertainty in our results and hence improve our measurement approach.

5. Conclusions and future research

This paper proposes a new measurement that expresses the degree to which an airport provides access to the air transport network by the average generalized travel cost occurring on air journeys from this airport. In a methodological perspective, we see the main contribution of this paper as follows.

First, our metric integrates the powers of "quality-weighted" and "shortest path" methodologies into one consistent framework. Its design incorporates information on route-specific service characteristics, details on the geographical position of an airport, and data on the temporal coordination of flights within the network. Furthermore, the method is the first connectivity metric for airports to implement rooftop modeling in its construction, which makes it capable of respecting passengers' preference for arrival time as the driver of airport connectivity. The mapping of alternative arrivals in a temporal perspective allows implementing effects from the temporal "distance" of successive arrivals on schedule delay. In addition, rooftop modeling mitigates the risk to inflate connectivity scores by counting connectivity contributions from routings that are not attractive to passengers. Finally, the measure's operationalization via generalized travel costs and their decomposition in individual cost components, makes its results easy to interpret and, therefore, suitable for a wide range of applications. The comparison of connectivity scores derived for different scenarios, for example, might enable policymakers and researchers to directly assess the welfare implications of policy initiatives that affect quality characteristics of air transport services and/or the physical structure of the air transport network.

In the second part of this paper, we demonstrate the potential of our method by application to a set of Scandinavia airports and map their connectivity scores based on their integration in the global air transport network in the period 2004 to 2018. Despite its regional focus on Scandinavia, the analysis also yields findings of generalizable character such as the importance of the geographical location of an airport as a driver of an airport's connectivity. Our results also indicate that existing "quality-weighted" metrics might systematically overestimate and "shortest-path" metrics underestimate the connectivity differences between airports.

With respect to the limitations of this study, future GTC-based connectivity measures might greatly benefit from research activities seeking to explore in more detail the factors that impact passengers' travel path choice if multiple options are available. In particular, how do passengers embrace the existence of alternative travel paths connecting the same O-D, and are passengers aware of the full set of alternatives in the first place? Are there substantial differences between leisure and business travelers? As our method assumes the perfectly cost-rational passenger, only travel paths that define the "minimum GTC curve" are directly contributing to an airport's connectivity score. All other paths are restricted to take effect only thought the competition term in the airfare formula. Future extensions of the model might incorporate this "option value" of alternative paths in a more advanced way. Another aspect worth future investigation is to analyze the importance of transfer airport characteristics (amenities, image, location, etc.) and the role that the likelihood of arrival delay has for passenger's travel path choice.

In terms of relevant model extensions, a next logical step could also be to implement the costs of airport access and egress to gain knowledge about the spatial dimension of airport catchment areas. Potential applications of our model might concern the socio-economic analysis of service-level alterations at airports and/or the impact assessment of environmental taxation schemes on the connectivity of different airports. In the latter case, an adjustment of Eqs. (2) and (3), for example by implementing a location specific taxation dummy, might allow the assessment of how such initiatives would change generalized travel costs at individual airports, given the existence of alternative travel paths that are not subject to such taxation.

CRediT authorship contribution statement

Falko Mueller: Conceptualization, Methodology, Software, Formal analysis. **Agaraoli Aravazhi:** Software.

Declaration of Competing Interest

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

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Appendix A

See Table A.1.

Table A.1
Block-time model.

	Dependent variable: Block time in minutes
GC-distance in miles	0.124***
	(0.00002)
Constant	31.164***
	(0.018)
Observations	430,311
Adjusted R^2	0.988
F Statistic	35,172,332.000*** (df = 1; 430309)

Note: *p < 0.1; **p < 0.05; ***p < 0.01; SE in parentheses.

Appendix B

See Table B.1.

Table B.1
Estimation results for airfare models (*Data Source:* Avinor (2017)).

	Dependent variable: Airfare in 2018 NOK (log)	
	Leisure travel purpose (1)	Business travel purpose (2)
Block time (min)	0.0039576***	0.0031723***
	(0.0039351/0.0039802)	(0.0031178/0.0032269)
Block time squared (min)	−0.0000018***	−0.0000013***
	(−0.0000018/−0.0000018)	(−0.0000014/−0.0000013)
Non-stop path – LCC	−0.2392991***	−0.4864364***
	(−0.2434872/−0.2351111)	(−0.4926992/−0.4801735)
Indirect path – LCC	−0.1499784***	−0.4746088***
	(−0.1568836/−0.1430733)	(−0.4867813/−0.4624363)
Non-stop path – monopoly	0.1008649***	0.1243361***
	(0.1008649/0.1092578)	(0.1179310/0.1307411)
Indirect path – monopoly	0.0719803***	0.1245271***
	(0.0650424/0.0789181)	(0.1155579/0.1334963)
One-stop path		0.1326747***
		(0.1231148/0.1422346)
Two-stop path		0.2572029***
		(0.2409266/0.2734792)

(*continued on next page*)

Table B.1 (*continued*)

	Dependent variable: Airfare in 2018 NOK (log)	
	Leisure travel purpose (1)	Business travel purpose (2)
Constant	6.4557410	6.9157940***
	(6.4513380/6.4601430)	(6.9102510/6.9213370)
Observations	442,670	240,524
R^2	0.484	0.465
Adjusted R^2	0.484	0.465
F Statistic	69,169.0***	26,170.3***
	(df = 4; 442665)	(df = 8; 240515)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; 95% confidence interval in parentheses.

Appendix C

See Table C.1.
See Table C.2.

Table C.1
Connectivity scores Scandinavian airports I/2018 (II/2018) and service features I/2018; – Part I.

			$GTCC_{2018/I}$		$GTCC_{2018/I}$ (segments)			Service features 2018/I		$GTCC_{2018/II}$	
Airport name	IATA code	Country	Global	% change to $GTCC_{2004/I}$	Dom.	Euro.	Icont.	Departures per week**	Link(s) to foreign hubs	Global	% change to $GTCC_{2004/II}$
Copenhagen	CPH	Denmark	582	−3.2	179	367	1131	2021	13	568	−4.7
Stockholm	ARN	Sweden	657	−7.3	284	432	1160	1907	13	648	−8.0
Oslo	OSL	Norway	664	−9.6	175	435	1179	2079	13	654	−7.4
Gothenburg	GOT	Sweden	675	−4.7	282	439	1232	514	11	674	−4.4
Billund	BLL	Denmark	689	−0.4	308	445	1249	255	8	684	−1.2
Helsinki	HEL	Finland	708	−6.4	197	481	1169	1541	13	693	−7.4
Aalborg	AAL	Denmark	741	−10.6	226	493	1288	143	3	740	−10.1
Stavanger	SVG	Norway	757	−0.6	193	514	1294	394	5	749	−0.4
Bergen	BGO	Norway	763	−5.6	178	521	1300	588	4	749	−4.3
Kristiansand	KRS	Norway	794	−9.1	243	539	1336	117	2	790	−4.3
Sandefjord	TRF	Norway	822	3.3	304	555	1355	180	2	818	3.7
Trondheim	TRD	Norway	833	−4.4	196	583	1347	470	4	821	−4.6
Aarhus	AAR	Denmark	844	4.6	282	574	1389	63	1	826	2.5
Turku	TKU	Finland	881	−0.3	229	625	1364	66	1	867	−3.6
Karup	KRP	Denmark	883	4.4	297	621	1374	46	0	931	6.6
Jönköping	JKG	Sweden	884	0.0	488	613	1397	39	1	918	−2.9
Ålesund	AES	Norway	893	−13	243	632	1407	115	1	864	−14.2
Malmö	MMX	Sweden	897	*	298	634	1428	170	1	896	*
Linköping	LPI	Sweden	900	−0.7	730	612	1436	20	1	899	−3.8
Tampere	TMP	Finland	916	1	224	653	1401	43	1	906	−1.3
Umeå	UME	Sweden	922	−7.8	317	667	1412	101	1	905	−7.9
Ørsta	HOV	Norway	922	−16.6	307	658	1413	48	0	931	−9.5
Haugesund	HAU	Norway	927	−0.3	276	659	1435	48	0	928	0.2
Oulu	OUL	Finland	933	−5.3	235	679	1388	97	0	931	−3.7
Molde	MOL	Norway	933	−8.8	267	665	1446	62	0	925	−8.6
Sønderborg	SGD	Denmark	935	*	309	665	1426	22	0	931	*
Stockholm	BMA	Sweden	935	−2.2	296	672	1433	418	1	941	−5.7
Foerde	FDE	Norway	939	−7.1	288	671	1439	41	0	927	−4.6
Visby	VBY	Sweden	939	−1.8	303	679	1447	67	0	912	−5.6
Östersund	OSD	Sweden	940	−7.5	334	678	1441	67	2	971	−3.2
Florø	FRO	Norway	943	−10	285	676	1440	50	0	922	−9.7
Vaasa	VAA	Finland	945	−1.8	255	685	1409	50	1	925	−3.8
Luleå	LLA	Sweden	948	−7.2	379	682	1443	97	0	938	−6.6
Kuopio	KUO	Finland	958	−7.0	249	699	1414	42	0	974	−4.2
Sogndal	SOG	Norway	963	−4.9	295	691	1466	53	0	988	−0.4
Stockholm	NYO	Sweden	975	−9.6	739	652	1618	101	0	937	−9.3
Skellefteå	SFT	Sweden	976	−6.2	421	702	1475	42	0	967	−3.5
Norrköping	NRK	Sweden	978	*	842	670	1535	11	1	980	*
Rovaniemi	RVN	Finland	981	−8.1	268	723	1426	42	1	977	−12.1

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Table C.1 (*continued*)

Airport name	IATA code	Country	$GTCC_{2018/I}$		$GTCC_{2018/I}$ (segments)			Service features 2018/I		$GTCC_{2018/II}$	
			Global	% change to $GTCC_{2004/I}$	Dom.	Euro.	Icont.	Departures per week**	Link(s) to foreign hubs	Global	% change to $GTCC_{2004/II}$
Örebro	ORB	Sweden	981	*	675	673	1552	11	1	1373	*
Kalmar	KLR	Sweden	982	*	347	716	1483	41	0	1001	*
Jyvaskyla	JYV	Finland	988	−1.9	275	723	1450	20	0	1001	−6.5
Sundsvall	SDL	Sweden	993	1.6	356	725	1493	62	0	998	1.7
Kristiansund	KSU	Norway	995	−6.1	297	721	1496	55	0	954	−8.2
Ronneby	RNB	Sweden	999	−4.1	354	725	1514	41	0	1011	−2.4
Tromsø	TOS	Norway	1002	−9.5	310	730	1492	338	4	987	−9.1
Bodø	BOO	Norway	1004	−7.3	275	732	1495	319	0	970	−7.8
Sandane	SDN	Norway	1005	*	348	725	1505	23	0	1016	*
Mariehamn	MHQ	Finland	1005	*	347	724	1496	28	1	1267	*
Røros	RRS	Norway	1005	*	349	721	1520	13	0	1004	*
Ängelholm	AGH	Sweden	1011	0.0	354	739	1512	59	0	1004	0.5
Harstad	EVE	Norway	1028	−10.3	314	751	1525	79	0	1007	−8.7

Note: * missing data; airport is not part of “consistent network”; ** based on constraints defined in *Section 3.2*.

Table C.2
Connectivity scores Scandinavian airports I/2018 (II/2018) and service features I/2018; – Part II.

Airport name	IATA code	Country	$GTCC_{2018/I}$		$GTCC_{2018/I}$(segments)			Service features 2018/I		$GTCC_{2018/II}$	
			Global	% change to $GTCC_{2004/I}$	Dom.	Euro.	Icont.	Departures per week**	Link(s) to foreign hubs	Global	% change to $GTCC_{2004/II}$
Karlstad	KSD	Sweden	1035	17.1	467	752	1532	32	0	1694	66.5
Joensuu	JOE	Finland	1035	−4.9	297	763	1502	24	0	1074	−2.0
Kajaani	KAJ	Finland	1046	−8.6	298	774	1508	25	0	1167	2.0
Pori	POR	Finland	1051	*	348	783	1487	26	1	*	*
Kiruna	KRN	Sweden	1077	−8.6	495	790	1570	20	0	1138	−4.8
Namsos	OSY	Norway	1090	−8.7	341	803	1586	26	0	1063	−6.6
Stord	SRP	Norway	1098	*	397	803	1603	13	0	1086	*
Bardufoss	BDU	Norway	1108	−6	367	815	1612	21	0	1077	−7.0
Kramfors	KRF	Sweden	1116	*	546	824	1603	11	0	*	*
Mo i Rana	MQN	Norway	1121	−10.6	375	837	1596	47	0	1103	−9.3
Sandnessjøen	SSJ	Norway	1126	−8.3	342	836	1629	31	0	1110	−6.4
Mosjøen	MJF	Norway	1131	−12.0	354	836	1642	27	0	1115	−9.0
Kokkola	KOK	Finland	1134	1.1	323	844	1618	24	1	1021	−10.8
Brønnøysund	BNN	Norway	1138	−2.4	346	848	1632	39	0	1106	−2.8
Rørvik	RVK	Norway	1139	−6.3	360	843	1646	22	0	1116	−3.5
Kittilä	KTT	Finland	1153	*	367	871	1603	20	3	1254	*
Leknes	LKN	Norway	1167	−10.8	403	871	1658	56	0	1155	−11.0
Ivalo	IVL	Finland	1170	*	343	868	1676	14	1	1356	*
Stokmarknes	SKN	Norway	1175	−10	414	879	1660	53	0	1174	−11.1
Kuusamo	KAO	Finland	1176	−15.4	338	877	1673	10	0	1300	−31.6
Alta	ALF	Norway	1178	−8.8	397	869	1706	60	0	1138	−10.1
Vilhelmina	VHM	Sweden	1191	*	596	900	1698	18	0	*	*
Kirkenes	KKN	Norway	1212	−9.2	423	895	1749	54	0	1162	−7.9
Lycksele	LYC	Sweden	1213	*	653	914	1683	12	0	*	*
Hammerfest	HFT	Norway	1222	−11.6	462	921	1700	85	0	1210	−12.3
Svolvær	SVJ	Norway	1228	−2.6	441	917	1736	55	0	1281	3.8
Halmstad	HAD	Sweden	1229	19.0	449	943	1704	18	0	1214	19.1
Växjö	VXO	Sweden	1230	34.5	439	946	1706	24	0	1000	3.4
Esbjerg	EBJ	Denmark	1230	8.6	748	895	1772	14	0	1242	8.8
Banak	LKL	Norway	1236	*	480	928	1728	18	0	1270	*
Andøya	ANX	Norway	1249	*	439	928	1784	36	0	1311	*
Trollhättan	THN	Sweden	1252	10.6	466	967	1739	20	0	1265	13.3
Borlange	BLE	Sweden	1281	*	748	960	1787	4	0	*	*
Sørkjosen	SOJ	Norway	1284	−17.6	545	983	1738	17	0	1275	−12.5
Örnsköldsvik	OER	Sweden	1322	*	683	988	1857	5	0	1022	*
Arvidsjaur	AJR	Sweden	1328	*	746	1011	1808	6	0	*	*
Værøy	VRY	Norway	1351	*	496	1034	1844	12	0	1335	*
Kemi-Tornio	KEM	Finland	1358	21.9	387	1041	1854	12	0	1489	30.2
Røst	RET	Norway	1368	*	505	1039	1886	12	0	*	*

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Table C.2 (*continued*)

			$GTCC_{2018/I}$		$GTCC_{2018/I}$(segments)			Service features 2018/I		$GTCC_{2018/II}$	
Airport name	IATA code	Country	Global	% change to $GTCC_{2004/I}$	Dom.	Euro.	Icont.	Departures per week**	Link(s) to foreign hubs	Global	% change to $GTCC_{2004/II}$
Valan	HVG	Norway	1400	−6.5	614	1083	1866	22	0	1390	−8.3
Vadsø	VDS	Norway	1406	−10.8	522	999	1822	63	0	1291	−7.4
Stockholm	VST	Sweden	1408	52.7	1205	979	2156	4	0	1385	23.0
Hasvik	HAA	Norway	1409	−11.3	517	1073	1938	17	0	1411	−10.7
Vardø	VAW	Norway	1461	−16.0	640	1130	1948	22	0	1434	−5.5
Mehamn	MEH	Norway	1478	−9	706	1159	1927	22	0	1457	−9.0
Hemavan	HMV	Sweden	1479	*	758	1147	1972	7	0	*	*
Båtsfjord	BJF	Norway	1513	−5.2	688	1180	1992	22	0	1501	−1.0
Berlevåg	BVG	Norway	1538	−6.7	718	4742	2014	16	0	1524	−3.4
Svalbard	LYR	Norway	1594	−14.9	624	1229	2149	6	0	1334	−14.3

Note: * missing data; airport is not part of "consistent network"; ** based on constraints defined in *Section 3.2*.

Appendix D

See Table D.1.
See Table D.2.

Table D.1
Connectivity scores Scandinavian airports I/2018 and cost components; – Part I.

			$GTCC_{2018/I}$	Cost components in USD					Cost components in %				
Airport name	IATA code	Country	Global	SD	IvT	Fare	TT	TP	SD	IvT	Fare	TT	TP
Copenhagen	CPH	Denmark	582	66	207	252	53	4	11.3	35.5	43.2	9.1	0.8
Stockholm	ARN	Sweden	657	69	238	276	68	5	10.5	36.3	42.1	10.3	0.8
Oslo	OSL	Norway	664	65	240	278	75	6	9.8	36.1	41.9	11.3	0.9
Gothenburg	GOT	Sweden	675	66	231	287	84	7	9.7	34.3	42.5	12.5	1.0
Billund	BLL	Denmark	689	64	232	294	92	7	9.3	33.7	42.6	13.3	1.1
Helsinki	HEL	Finland	708	70	258	300	75	6	9.9	36.4	42.3	10.6	0.8
Aalborg	AAL	Denmark	741	69	246	302	115	10	9.3	33.2	40.7	15.5	1.3
Stavanger	SVG	Norway	757	75	256	305	112	9	9.9	33.8	40.3	14.7	1.2
Bergen	BGO	Norway	763	69	262	310	113	10	9.0	34.3	40.6	14.8	1.3
Kristiansand	KRS	Norway	794	74	264	313	133	11	9.3	33.2	39.4	16.8	1.3
Sandefjord	TRF	Norway	822	88	274	322	129	11	10.7	33.3	39.1	15.6	1.3
Trondheim	TRD	Norway	833	77	286	331	128	11	9.2	34.3	39.7	15.4	1.3
Aarhus	AAR	Denmark	844	101	258	317	156	12	11.9	30.6	37.6	18.5	1.4
Turku	TKU	Finland	881	79	287	347	156	12	9.0	32.6	39.4	17.7	1.4
Karup	KRP	Denmark	883	92	275	317	186	12	10.4	31.2	35.9	21.1	1.4
Jönköping	JKG	Sweden	884	105	284	310	175	10	11.9	32.1	35.1	19.8	1.2
Ålesund	AES	Norway	893	93	291	333	164	12	10.4	32.6	37.3	18.3	1.4
Malmö	MMX	Sweden	897	91	294	333	166	12	10.2	32.8	37.1	18.5	1.4
Linköping	LPI	Sweden	900	77	294	362	156	10	8.6	32.7	40.2	17.3	1.1
Tampere	TMP	Finland	916	90	293	351	169	12	9.8	32.0	38.4	18.5	1.3
Umeå	UME	Sweden	922	90	302	349	168	13	9.8	32.8	37.8	18.3	1.4
Ørsta	HOV	Norway	922	93	306	344	165	14	10.1	33.2	37.3	17.9	1.5
Haugesund	HAU	Norway	927	97	298	333	186	14	10.5	32.1	35.9	20.0	1.5
Oulu	OUL	Finland	933	79	315	370	155	13	8.5	33.8	39.7	16.7	1.4
Molde	MOL	Norway	933	102	298	334	185	14	10.9	32.0	35.8	19.8	1.5
Sønderborg	SGD	Denmark	935	104	295	351	173	12	11.1	31.6	37.6	18.5	1.3
Stockholm	BMA	Sweden	935	118	278	318	209	13	12.6	29.7	34.0	22.4	1.3
Foerde	FDE	Norway	939	93	292	350	192	13	9.9	31.1	37.3	20.4	1.4
Visby	VBY	Sweden	939	103	304	338	181	14	10.9	32.4	36.0	19.3	1.4
Östersund	OSD	Sweden	940	92	302	358	175	13	9.8	32.2	38.1	18.6	1.4
Florø	FRO	Norway	943	109	301	340	178	14	11.6	31.9	36.1	18.9	1.5
Vaasa	VAA	Finland	945	92	306	373	161	12	9.8	32.4	39.4	17.1	1.3
Luleå	LLA	Sweden	948	89	318	357	171	13	9.4	33.6	37.7	18.0	1.4
Kuopio	KUO	Finland	958	94	308	377	166	13	9.8	32.1	39.4	17.3	1.4
Sogndal	SOG	Norway	963	116	299	347	185	15	12.1	31.1	36.0	19.2	1.6
Stockholm	NYO	Sweden	975	101	313	344	205	12	10.4	32.1	35.3	21.0	1.3
Skellefteå	SFT	Sweden	976	105	314	355	189	13	10.7	32.2	36.4	19.4	1.4

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Table D.1 (*continued*)

Airport name	IATA code	Country	$GTCC_{2018/I}$ Global	Cost components in USD SD	IvT	Fare	TT	TP	Cost components in % SD	IvT	Fare	TT	TP
Norrköping	NRK	Sweden	978	127	316	342	181	11	13.0	32.3	35.0	18.5	1.2
Rovaniemi	RVN	Finland	981	88	331	385	165	13	9.0	33.7	39.2	16.8	1.3
Örebro	ORB	Sweden	981	132	284	350	203	13	13.5	28.9	35.7	20.7	1.3
Kalmar	KLR	Sweden	982	104	305	363	197	13	10.6	31.0	37.0	20.1	1.3
Jyvaskyla	JYV	Finland	988	100	311	382	182	13	10.1	31.5	38.7	18.4	1.3
Sundsvall	SDL	Sweden	993	129	300	353	198	13	13.0	30.2	35.6	19.9	1.3
Kristiansund	KSU	Norway	995	114	306	355	206	14	11.5	30.7	35.7	20.7	1.4
Ronneby	RNB	Sweden	999	111	303	362	208	14	11.1	30.4	36.3	20.9	1.4
Tromsø	TOS	Norway	1002	95	346	375	173	13	9.5	34.5	37.4	17.2	1.3
Bodø	BOO	Norway	1004	103	331	365	191	14	10.3	32.9	36.4	19.0	1.4
Sandane	SDN	Norway	1005	113	312	370	192	18	11.2	31.1	36.8	19.1	1.8
Mariehamn	MHQ	Finland	1005	127	306	340	218	14	12.6	30.4	33.9	21.7	1.4
Røros	RRS	Norway	1005	123	293	338	236	14	12.3	29.2	33.7	23.5	1.4
Ängelholm	AGH	Sweden	1011	113	313	372	200	14	11.1	30.9	36.8	19.8	1.4
Harstad	EVE	Norway	1028	102	345	372	194	14	10.0	33.6	36.2	18.9	1.4

Note: Schedule delay (SD), in-vehicle time (IvT), airfare (Fare), transfer time (TT), transfer penalty (TP).

Table D2
Connectivity scores Scandinavian airports I/2018 and cost components; – Part II.

Airport name	IATA code	Country	$GTCC_{2018/I}$ Global	Cost components in USD SD	IvT	Fare	TT	TP	Cost components in % SD	IvT	Fare	TT	TP
Karlstad	KSD	Sweden	1035	113	322	388	199	13	11.0	31.1	37.4	19.2	1.3
Joensuu	JOE	Finland	1035	149	301	338	234	13	14.4	29.1	32.6	22.6	1.3
Kajaani	KAJ	Finland	1046	102	333	405	194	13	9.7	31.8	38.7	18.5	1.3
Pori	POR	Finland	1051	158	307	342	232	13	15.0	29.2	32.5	22.0	1.2
Kiruna	KRN	Sweden	1077	110	342	397	214	15	10.2	31.7	36.8	19.8	1.4
Namsos	OSY	Norway	1090	127	327	364	255	17	11.6	30.0	33.4	23.3	1.6
Stord	SRP	Norway	1098	140	315	350	279	14	12.7	28.7	31.9	25.4	1.3
Bardufoss	BDU	Norway	1108	116	351	380	248	14	10.4	31.7	34.3	22.3	1.3
Kramfors	KRF	Sweden	1116	158	321	355	269	14	14.2	28.7	31.8	24.1	1.2
Mo i Rana	MQN	Norway	1121	113	357	389	243	18	10.0	31.9	34.7	21.7	1.6
Sandnessjøen	SSJ	Norway	1126	123	348	379	257	20	10.9	30.9	33.6	22.9	1.7
Mosjøen	MJF	Norway	1131	111	348	375	278	19	9.8	30.8	33.2	24.6	1.7
Kokkola	KOK	Finland	1134	134	330	396	261	13	11.8	29.1	34.9	23.0	1.1
Brønnøysund	BNN	Norway	1138	141	342	375	260	19	12.4	30.1	33.0	22.9	1.7
Rørvik	RVK	Norway	1139	114	338	396	270	21	10.0	29.7	34.7	23.7	1.9
Kittilä	KTT	Finland	1153	131	361	413	234	14	11.4	31.3	35.8	20.3	1.2
Leknes	LKN	Norway	1167	125	366	393	262	21	10.7	31.4	33.7	22.4	1.8
Ivalo	IVL	Finland	1170	130	351	413	264	13	11.1	30.0	35.3	22.6	1.1
Stokmarknes	SKN	Norway	1175	121	375	407	252	21	10.3	31.9	34.6	21.4	1.8
Kuusamo	KAO	Finland	1176	140	336	408	279	13	11.9	28.6	34.7	23.7	1.1
Alta	ALF	Norway	1178	123	372	409	256	18	10.4	31.6	34.8	21.7	1.5
Vilhelmina	VHM	Sweden	1191	168	343	374	292	14	14.1	28.8	31.4	24.5	1.1
Kirkenes	KKN	Norway	1212	127	382	408	278	16	10.5	31.5	33.7	23.0	1.3
Lycksele	LYC	Sweden	1213	179	341	373	306	14	14.8	28.1	30.7	25.2	1.1
Hammerfest	HFT	Norway	1222	116	391	419	275	21	9.5	32.0	34.3	22.5	1.7
Svolvær	SVJ	Norway	1228	118	373	411	305	21	9.6	30.3	33.5	24.8	1.8
Halmstad	HAD	Sweden	1229	138	364	440	267	20	11.2	29.6	35.8	21.7	1.7
Växjö	VXO	Sweden	1230	154	355	415	288	19	12.5	28.8	33.7	23.4	1.5
Esbjerg	EBJ	Denmark	1230	182	345	381	306	16	14.8	28.1	31.0	24.9	1.3
Banak	LKL	Norway	1236	126	398	417	275	21	10.2	32.2	33.7	22.2	1.7
Andøya	ANX	Norway	1249	121	383	410	313	22	9.7	30.7	32.8	25.1	1.8
Trollhättan	THN	Sweden	1252	163	358	424	288	20	13.0	28.6	33.8	23.0	1.6
Borlange	BLE	Sweden	1281	275	320	371	299	16	21.5	25.0	29.0	23.3	1.2
Sørkjosen	SOJ	Norway	1284	163	383	427	289	22	12.7	29.8	33.3	22.5	1.7
Örnsköldsvik	OER	Sweden	1322	181	367	437	322	21	13.7	27.6	32.9	24.2	1.6
Arvidsjaur	AJR	Sweden	1328	138	378	416	398	22	10.2	28.0	30.8	29.4	1.6
Værøy	VRY	Norway	1351	113	374	427	429	15	8.3	27.6	31.4	31.6	1.1
Kemi-Tornio	KEM	Finland	1358	122	385	423	413	26	8.9	28.2	30.9	30.2	1.9
Røst	RET	Norway	1368	175	414	495	288	28	12.5	29.6	35.4	20.6	2.0
Valan	HVG	Norway	1400	216	418	455	292	25	15.3	29.8	32.3	20.8	1.8

(*continued on next page*)

Table D2 (*continued*)

Airport name	IATA code	Country	$GTCC_{2018/I}$ Global	Cost components in USD SD	IvT	Fare	TT	TP	Cost components in % SD	IvT	Fare	TT	TP
Vadsø	VDS	Norway	1406	244	332	362	370	14	18.4	25.1	27.4	28.0	1.1
Stockholm	VST	Sweden	1408	195	358	373	467	14	13.9	25.5	26.5	33.2	1.0
Hasvik	HAA	Norway	1409	155	413	456	358	27	11.0	29.3	32.3	25.4	1.9
Vardø	VAW	Norway	1461	161	413	466	393	28	11.0	28.3	31.9	26.9	1.9
Mehamn	MEH	Norway	1478	169	436	527	311	36	11.4	29.5	35.7	21.0	2.4
Hemavan	HMV	Sweden	1479	151	391	455	460	22	10.2	26.4	30.8	31.1	1.5
Båtsfjord	BJF	Norway	1513	159	438	507	373	36	10.5	29.0	33.5	24.7	2.4
Berlevåg	BVG	Norway	1538	161	440	505	398	35	10.5	28.6	32.8	25.9	2.2
Svalbard	LYR	Norway	1594	236	442	471	427	18	14.8	27.8	29.6	26.8	1.1

Note: Schedule delay (SD), in-vehicle time (IvT), airfare (Fare), transfer time (TT), transfer penalty (TP).

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