TRAFFIC RELATED REPRESENTATIVE AIRPORT CATEGORIES FOR TECHNOLOGY IMPACT EVALUATION

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Abstract

Technology impact evaluations in air transport require the specification of environment conditions, such as the traffic structure. Since a multitude of worldwide traffic situations exists, this paper presents a systematic approach based on cluster analysis that can handle the worldwide diversity, while ensuring to determine most relevant traffic situations. This is crucial for the universality and global relevance of evaluation results. The approach is presented for the application example of runway capacity evaluation, as part of which features of daily movement distributions of airports and the traffic mix as well as peak situations are quantified. The resulting representative airport and peak categories comprise a limited set of typical traffic situations worldwide that can serve as standard input for capacity-related evaluation, ensuring comparability and clarity.

Keywords: Airport, categorization, representative, air traffic

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1. INTRODUCTION

Evaluation of the impact of new technologies in air transportation is important to ensure an efficient transport system in the future. Moreover, it is crucial to determine this impact on a global level to cover a range of potential environment conditions faced and to evaluate whether a certain technology or concept proves its potential. The specification of environment conditions for these evaluations has a considerable influence on the results and needs to be pursued thoroughly and systematically. A major problem to be faced is the worldwide diversity in traffic conditions that has to be handled. It is not possible to cover each and every specific environment condition in impact analyses since this is computationally demanding. However, a reduction of environments to a few specific local ones is also not beneficial as it focuses on local peculiarities that do not reflect the global range of environments. Therefore, this paper provides a systematic approach to determine global representative environment conditions. Since the approach is application specific, runway capacity impact evaluation is addressed as an example.

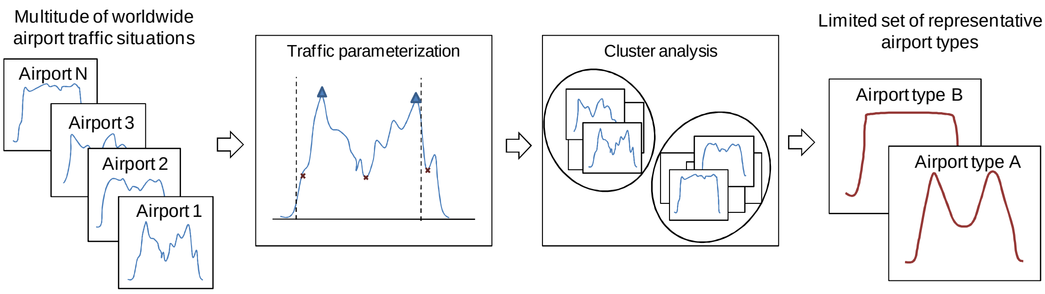
Evaluation of aircraft concepts in their operational environment, such as runway capacity analyses, and their impact created requires the traffic structure at an airport as one of the main environment inputs. This includes the daily airport traffic as well as traffic peaks that occur. The example of runway capacity impact was considered, since the runway system is one of the most constraining elements influencing airport capacity (Böck and Hornung, 2012). Böck (2013) focused on the evaluation of capacity impact of aircraft concepts based on selected real airport environments only. He mentioned the need of further addressing the diversity in traffic situations to ensure more generalized results. As explained above, selection of particular real airports is not the most favorable solution for assessments on a technological level since the specification of most suitable real airports is difficult and each real airport will incorporate peculiarities in the analysis process that influence the results. In order to evaluate aircraft concepts in a global perspective, a set of representative airport categories with distinct application-specific traffic characteristics could provide this desired input.

Before deriving individual categorizations of airports, existing ones were elaborated. A variety of definitions for airport categorizations can already be found worldwide. A review of existing categorizations was presented in Öttl and Böck (2011), along with a judgment of applicability of these categorizations for air traffic-related simulations and analyses. For these kinds of applications the quantified description of operational or traffic-related characteristics was found to be an important criterion. However, existing categorizations do not sufficiently describe traffic-related features, but rather contain qualitative descriptions or specifications related to passenger numbers only. This analysis already pointed out the need for application-specific airport categorizations based on similar traffic characteristics and not on passenger numbers or other qualitative features not related to the intended application.

In a first approach to address similarities in air traffic at airports, Öttl et al. (2013) presented an evaluation of worldwide airport peak situations for use in runway capacity analyses. By application of a cluster analysis, similar groups of traffic peaks could be determined and a representative limited set of peak situations could be specified. This idea of deriving typical worldwide traffic situations is extended in this paper and addressed on an airport level rather than for peak traffic situations only. The work of Öttl et al. (2013) only covered an analysis of air traffic peaks at airports. These were characterized by their traffic mix. However, it was already mentioned that a capacity impact analysis requires daily traffic structures at airports in addition to the peaks. Hence, in the current paper the focus is on the derivation of representative airport categories based on parameters describing the daily traffic characteristics at airports. Additionally, the cluster analysis process is further improved compared to previous work and the data basis further extended.

An overview of the process of deriving representative environment conditions (i.e. traffic-related representative airport categories in the application context) is shown in Figure 1.

Figure 1: Overview of the Approach to derive Traffic-Related Representative Airport Categories



Notes: Traffic characteristics at airports are parameterized and clustered. This reduces the multitude of airport traffic situations worldwide to a limited number of representative cases.

This systematic process identifies similarities in a multitude of traffic situations worldwide, which serve as the basic input. In order to pursue this, a cluster analysis is applied for which it is necessary to determine relevant parameters that describe the traffic environment. These parameters mainly depend on the intended application of the resulting airport categories. The cluster analysis results in a limited set of representative airport types, which enables a clear and comparable traffic-related analysis and can be considered as a standardized input.

The specification of relevant parameters to describe the traffic environment is not straightforward. Hence, this traffic parameterization is explained in detail in section 2, while section 3 outlines the cluster analysis process applied to determine an optimal number of groups of similar airports and peaks. Section 4 provides the resulting airport clusters for airport capacity related evaluations.

2. TRAFFIC PARAMETERIZATION

The cluster analysis incorporated in the presented approach requires a clear quantification and parameterization of the environment conditions of relevance. Hence, before traffic-related similarities in airports can be identified for the application example, it is necessary to determine appropriate similarity parameters that are of importance in this context and at the same time are suitable to characterize the differences in traffic features among airports.

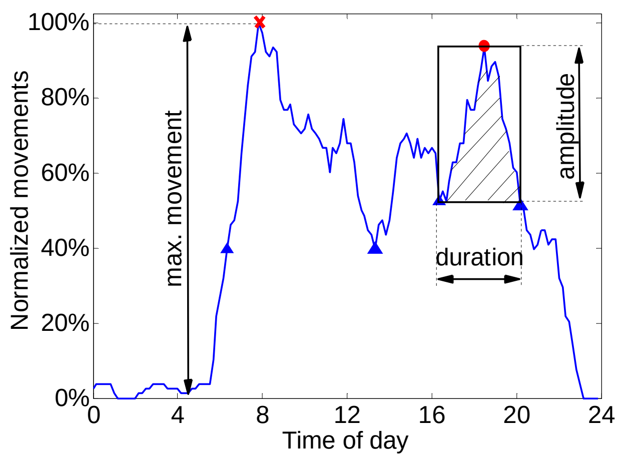
The main sources of parameters to be taken into account are the technology evaluation methods for which the resulting representative environment conditions are intended to be applied. On the one hand, parameters can be directly incorporated as a similarity measure for clustering in case the data basis for them is available and there is a clear way to determine them (e.g. percentage of heavy aircraft movements in one day). On the other hand, there are cases where one specific parameter cannot be directly determined or where several parameters are required to specify a certain situation (e.g. parameters that characterize the movement distribution in one day). In these cases new parameters or metrics can be defined. In the following, similarity parameters of importance for runway capacity related technology evaluation are discussed.

2.1 Traffic Parameters for Capacity-related Application

The methodology used for runway capacity impact evaluation is considered as given, being described in Böck and Hornung (2012). From this method the required input parameters characterizing the evaluation environment can be specified. General traffic parameter needs for runway capacity related technology evaluation were also mentioned in previous publications of this application context (see Öttl and Böck, 2011; Öttl et al., 2013). As mentioned earlier, both traffic peaks and daily airport traffic are considered in this approach. A further important element of the evaluation environment for capacity analysis is the runway system, i.e. the infrastructure. However, in this paper only relative traffic-related characteristics are considered, not taking into account infrastructure features. This decoupled assessment was also proposed by Böck et al. (2011). Nevertheless, an analysis of relevant infrastructure layouts on a global level is important for capacity analysis, but is independent of the findings in this work.

In Öttl et al. (2013) it was shown that peak traffic situations can show similarities across different types or sizes of airports, when considering the traffic structure in terms of the aircraft mix only. However, that analysis did not consider any information that describes the peak shape, which is also important to characterize a peak traffic situation. Moreover, peak situations can vary significantly during a one week period, depending on the type of airport. Therefore, it is advisable to take a whole week of scheduled traffic into account (see also section 2.2). To describe a peak situation, certainly the aircraft mix is incorporated as a main feature. Similar to the development in Öttl et al. (2013) 10 aircraft weight classes based on an analysis of maximum take-off weight of currently operating aircraft types (see also Figure 11 in Appendix) were incorporated as the parameters to describe the peak mix. Since arriving and departing traffic can show significantly different shares in a peak situation, it is important to distinguish between these two. The final set of similarity parameters for traffic peak situations also contains peak shape-related parameters. In an analysis of a variety of potential parameters regarding their suitability as a similarity measure the following three have been selected: peak duration in hours, peak fill factor and peak amplitude as percentage of the maximum peak at the respective airport. The three parameters are shown in Figure 2. The fill factor specifies the area under the peak in relation to the area of a rectangle, given by the minimum and maximum peak deflection. The peak amplitude is determined relative to the maximum peak at the airport to allow for a dimensionless assessment of airports of different movement numbers. The identification of a traffic peak in a daily movement distribution is performed by an automated algorithm, allowing for an analysis of a large amount of airports. The underlying steps are not explained further, since they would go beyond the scope of this paper. However, it should be mentioned that existing definitions of a typical peak situation (e.g. Standard Busy Rate in Ashford et al., 1991) do not play a significant role in this context. These are mainly based on passenger numbers or focusing on a period of an entire year rather than the daily traffic structure. To be able to incorporate a large amount of airports, peak detection is based on daily movement distributions determined from OAG flight data (OAG, 2008).

Figure 2: Illustration of Parameters to describe a Traffic Peak Shape



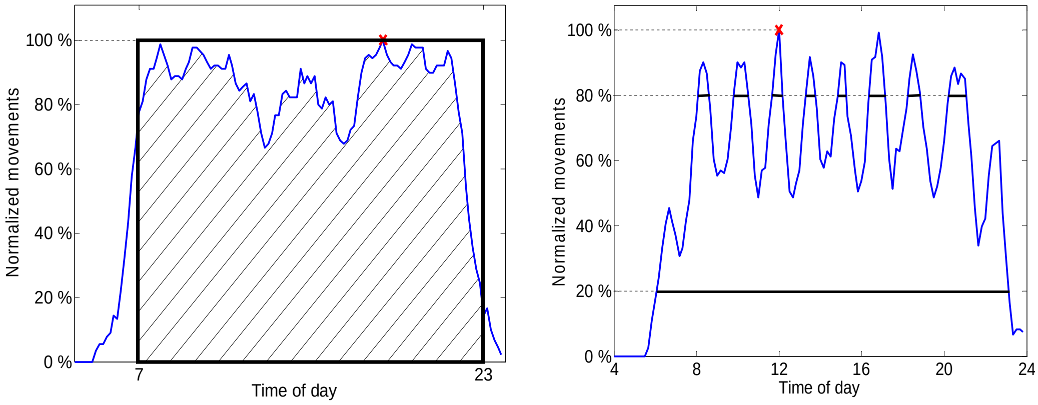
Notes: Triangles mark the start and end points of peaks, the red dot is a peak maximum and the cross marks the maximum peak at the airport.

Apart from peak traffic situations there are additional traffic characteristics of importance for capacity-related technology evaluation. First, the total daily traffic mix at an airport should be considered for an analysis. Therefore, the 10 aircraft weight classes are considered again. As a major difference to peak situations, the daily traffic does not require a differentiation into arrivals and departures, since both should be close to equal during one day of operation. The distribution of aircraft movements during one day should also be taken into consideration for a capacity-related airport categorization. From these distributions different characteristics can be identified, e.g. whether traffic peaks occur and how many of them. Moreover, periods of high traffic load can be determined. The parameterization of the daily movement distribution is an example for which no pre-defined clear parameters exist. Airport categorizations based on movement-related features have not been specified before. In an extensive study a multitude of parameters or metrics have been specified that characterize certain features of this daily distribution. By analyzing the suitability as a similarity measure, e.g. by clustering of a single parameter, and expert judgment, the number of parameters could be reduced to the most relevant that are explained in the following. In order to allow for an analysis independent of the actual absolute size of an airport, parameters referring to the number of movements were specified relative to the maximum number of movements at the respective airport.

The number of peaks (NP) states how often peak situations occur in the daily traffic characteristics. Besides determination of the number of peak situations in the total movement distribution, also the peaks in arrival and departure distributions are of interest for traffic-related investigations. The fill factor (FF) of the daily movement distribution is derived similar to the peak fill factor. It represents the area under the movement distribution graph in the time period from 7:00 to 23:00 (local time, LT), divided by the area of a rectangle given by the maximum movement number at that day at the respective airport (see hatched area share of rectangle in Figure 3, left). This fill factor allows an identification of airports with high total loads during the day and is a measure of how much of a fictitious movement limit is already used up. Of course, the significance of the fill factor would be highest when official capacity limits of airports were used. Unfortunately, these are not generally available for a large airport dataset. Hence, the maximum number of movements is a reasonable reference. Since for almost all airports traffic load issues arise primarily during the day, the fill factor was defined for a frequently used time period of day (7:00-19:00 LT) and evening (19:00-23:00 LT) (EC, 2002).

In contrast to the fill factor the parameter relative load (RL) provides information on the amount of time where flight activities reach a high number of movements. These are usually allocated to peak situations. Therefore, the time period of flight activities at or above 80% of the maximum movement number, resembling a high load condition, are determined and set into relation to the time period for 20%, which was specified as a general operating condition of low traffic load (see Figure 3, right). A low value indicates that only certain peak situations reach high load values, while a value close to 100% states that the airport constantly operates under high load conditions (compare also Figure 4).

Figure 3: Illustration of the Parameters Fill Factor (left) and Relative Load (right)

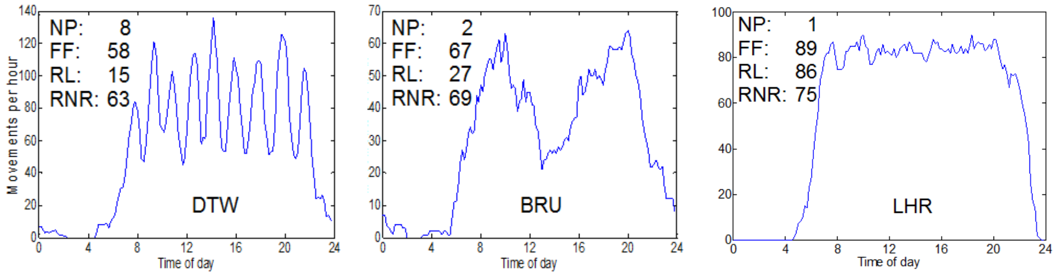


Notes: The fill factor is the ratio between the hatched area under the movement graph and the rectangle specified by the maximum number of movements (indicated as 100%). The relative load relates the duration in which flights occur at and above 80% of max. movements to a lower limit of 20%.

For determining the relative night rest (RNR) parameter the frequently used definition of the night time period (23:00-07:00 LT) is considered (EC, 2002). Analyzing this time period, the total duration in which the movement numbers are below 5 in 30min intervals is considered the night rest period, since movement numbers are significantly low (only few freighter or mail flights can occur). This duration is then set into relation to the total 8h night time period again. A value of 100% states that there are no significant movement numbers in the night period.

In order to illustrate the ability of the parameters described to characterize significant features of movement distributions, Figure 4 shows three very distinct airport examples along with their parameter values for a single day. It can be observed that peak number and the relative load are able to describe the peak characteristics, while the fill factor provides a value for how much of the daily distribution is “filled” to a limit. While the parameters mentioned describe day time features, the relative night rest finally provides information about the night time period, the latter of which shows only minor differences in the examples presented.

Figure 4: Three Examples of Significantly Distinct Daily Movement Distributions along with their Parameter Values



Notes: NP: number of peaks, FF: fill factor in %, RL: relative load in %, RNR: relative night rest in %.

2.2 Specification of Data Samples

The similarity parameters need to be determined for a large-enough dataset of airports for cluster analysis. This airport dataset shall contain a variety of airports worldwide that are of relevance for similarity assessment. Analyzing the ACI report 2007, it could be determined that 90% of worldwide passenger traffic is accommodated at only 302 airports worldwide. In comparison, 473 airports account for 90% of worldwide aircraft movements. Hence, a reasonable airport dataset was specified by the intersection of the two specifications, resulting in 287 airports. This dataset contains a wide range of airports worldwide with highest movement and passenger numbers, relevant for technology evaluation.

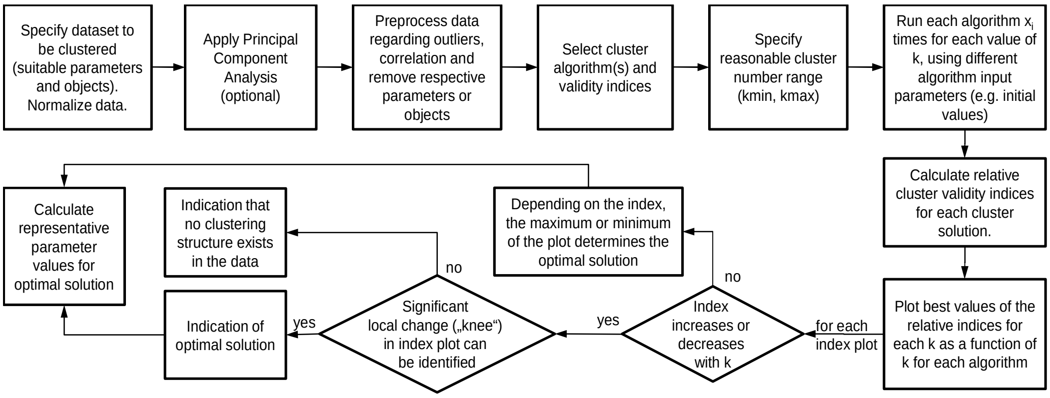
Particularly for the capacity-related assessment, the airport dataset had to be further reduced, since the 287 airports still contained a considerable amount of airports with very low movement numbers per hour, for which the peak detection algorithm resulted in errors. Comparing a visual error classification of peak detection with the maximum number of movements occurring at the respective airport, airports below a maximum of 16 movements per hour should be removed. Taking into account that lowest official numbers for slot facilitated airports in Germany are at 18 movements per hour, this limit was incorporated, resulting in a final airport dataset of 203 airports.

To determine the traffic parameters for the airports selected, OAG traffic data available for the year 2008 is used. Usually, the summer season shows higher movement numbers due to holiday travel. Hence, this season was considered, as critical peak situations and movement distribution features are reflected more clearly during summer season. Analyzing daily hourly movement distributions of airports during a whole week showed that there can be considerable variations, especially regarding the occurrence and characteristics of peak situations. Hence, seven consecutive days of scheduled movement data from OAG were taken into account. Airports with significant deviations during a week, e.g. Paris Orly or Las Palmas, can be considered as distinct airports in terms of varying movement characteristics. In order not to apply artificial weighting to airports that show weekly variations, each day is treated as a separate airport for the whole airport dataset (e.g. MUC1 to MUC7). Analyzing OAG data, it could be determined that the months of June, July and September 2008 showed highest worldwide movement numbers of that year. Since in previous studies the busiest day of the year for Munich Airport in June 2008 was used, the week containing this day was taken into account for the final analysis.

3. CLUSTER ANALYSIS

A systematic approach to find similar groups of objects in a dataset by use of cluster analysis was already introduced for the traffic peak analysis in Öttl et al. (2013). In the current paper, the cluster analysis process is further improved and extended, for instance by incorporating several cluster algorithms. The stepwise process of cluster analysis applied in this paper is presented in Figure 5. It starts with the selection of similarity parameters and data objects. Generally speaking, the smaller the number of similarity parameters, the smaller the number of objects required to get reasonable cluster results (referred to as "curse of dimensionality" (Theodoridis, 2009). A standardization of cluster data to a mean of zero and a variance of one is applied to avoid an artificial weighting of certain parameters due to their difference in magnitude. Moreover, this is essential for the subsequent optional step of Principal Component Analysis (PCA). PCA is a technique to transform data variables into a new set of variables – the principal components – which are linear combinations of the original variables and uncorrelated among themselves. The principal components are specified such that the data variance is maximized for the first component and the remaining variance is accounted for by the subsequent components. Hence, they are ordered by the magnitude of data variance they comprise. Considering only a subset of the principal components for further analysis can serve as a data reduction technique compared to taking into account all original variables, while still incorporating components of highest data variance. Due to the presented features, application of PCA before clustering can help to identify reasonable cluster solutions more clearly. For a detailed description of PCA refer to Sharma (1996).

Figure 5: Stepwise Cluster Analysis Approach (k denotes the Number of Clusters)



Notes: The process includes data preprocessing, application of cluster algorithms and an assessment to identify the optimal cluster solution (cluster validity process based on Halkidi et al. 2001).

In the pre-processing step, the input dataset is analyzed regarding the correlation between parameters and regarding outlier objects. In case a PCA is applied to the data, no correlations will occur. Outliers can distort the results and, thus, should be removed. Various methods for outlier detection exist in literature, of which the Local Outlier Factor (Breuning et al. 2000) was selected.

The type of cluster algorithm used largely depends on the data to be clustered without a universally applicable best cluster algorithm. Hence, it is recommended to take into account several applicable algorithms and compare the results (Sharma 1996). There is a large variety of cluster algorithms, some of which are applicable with certain restrictions only. An algorithm can, for instance, be intended for large datasets only. However, specification of dataset size differs. Since the number of airports addressed in this paper constitutes a small to medium size dataset compared to the specifications in Han et al. (2012) and Abu Abbas (2008), algorithms specifically mentioned to be applicable to this type of data were considered. Han et al. (2012) stated that partitioning methods, such as k-means, are effective for these dataset sizes. Abu Abbas (2008) concluded that hierarchical algorithms and self-organized maps are recommended for small datasets. Moreover, it was important that the algorithms are easily implementable and show a low demand in computation time. Hence, k-means and k-medoid (PAM) – two partitioning methods – and agglomerative hierarchical clustering were finally selected. For a description of the algorithms refer to literature (e.g. Gan et al. 2007, Han et al. 2012 or Theodoridis et al. 2009).

The behaviour of many cluster algorithms depends on features of the dataset analyzed as well as initial conditions and parameters required for the method (Halkidi et al. 2001). Therefore, several cluster approaches are necessary, followed by a so-called cluster validity assessment to identify a potential optimal cluster result. Moreover, many cluster algorithms require the number of clusters to be specified beforehand, which is usually not possible, since this number is also among the results. Thus, Halkidi et al. (2001) presented a process of cluster validity assessment incorporated in this paper and accounting for the remaining steps in Figure 5. It is proposed to repeat each algorithm for different cluster numbers k and different algorithm input parameters (mainly initial conditions). For each of the results, cluster validity indices can be calculated. Many indices have been defined and analyzed in literature (see also Halkidi et al. 2001 and Theodoridis et al. 2009). The indices taken into consideration for this approach are the Calinski-Harabasz (CH), Davies-Bouldin (DB), Dunn (DI) and I-Index (I), of which the first three are widely known. In a performance study by Maulik et al. (2002) the I-Index was described as the most reliable of the mentioned indices and hence has been included in the analysis process. Plotting the maximum (or minimum) of the respective index versus the number of clusters can help to identify an optimum. In case a clear global optimum cannot be identified, also local optima or “kinks” in the graphs can be an indication for an optimal cluster result. Of course, there is still a certain part of subjectivity in the interpretation of the quality of a clustering result and different indices can result in distinct potential optima. However, this approach offers a systematic way of addressing this issue.

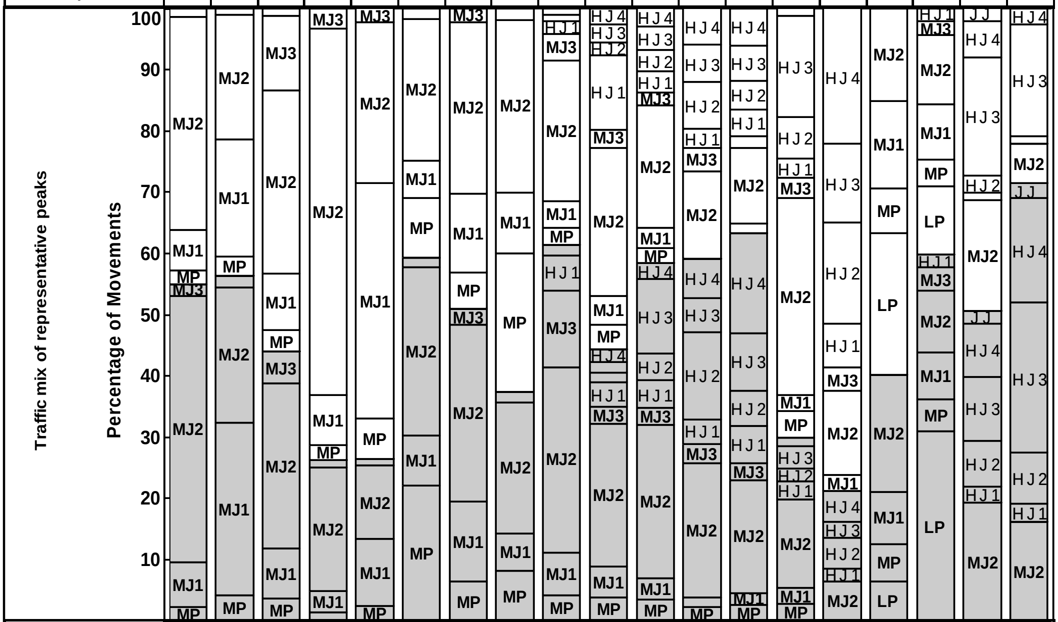
4. REPRESENTATIVE AIRPORT AND PEAK CATEGORIES FOR CAPACITY RELATED APPLICATION

The cluster analysis approach presented above was applied to the example application of airport capacity related technology evaluation. Since all of the similarity parameters mentioned in section 2.1 (peak related, airport traffic mix and movement distribution related) are of interest for a capacity-related airport categorization, it would be optimal to take all of them into consideration at once. Unfortunately, the more parameters are taken into consideration for clustering, the harder it is to determine distinct groups of similar characteristics. Hence, it was decided to apply the presented cluster approach separately to an airport dataset and a peak dataset and combine the results afterwards. Peak-related parameters are specified with reference to a peak situation only and do not depend directly on parameters of the daily airport traffic at the respective airport of occurrence. Therefore, this separation is reasonable. Nevertheless, peaks reflect some of the characteristics of the airport daily traffic and hence a later recombination is useful.

The peak cluster assessment resulted in an optimal solution of 19 representative traffic peak situations. Resulting parameter values are shown in Figure 6. Labels for aircraft weight classes are provided for values ≥ 2% for clarity. Traffic mix shares for departures and arrivals (shaded in gray) are provided separately. Peaks are presented in their order of cluster size, being the number of original peaks that formed the clusters. It can be observed that the results contain significant arrival and departure peaks and that the most representative peaks do not contain heavy aircraft traffic. The fact that strong variations in the arrival/departure ratio result is positive, since it reflects the actual range of ratios occurring in reality. As a main difference to the assessment in Öttl et al. (2013), the optimal number of clusters is slightly changed. This is mainly due to the additional shape parameters added and the extended airport data basis. However, comparing the features of the clusters clear similarities can be observed. The additional shape parameters are provided in the table in Figure 6. The resulting peak duration is between 2.5 and 3.1 h for most of the peaks, with the major exception of peak type 7. This cluster contains airports reaching capacity limits during certain periods (e.g. Frankfurt). It has to be mentioned that the peak duration is defined as the bottom peak duration and not as the duration at the top movement number of the peak. The fill factor can then provide additional information on the degree of pointedness of the traffic situation. A peak situation with high relative amplitude is preceded and/or followed by a situation of lower absolute movement numbers compared to peak situations with low relative amplitude. In general, peaks with lower relative amplitude offer fewer possibilities for recovering from delays or movement shifts after the peak situation and are thus most critical in terms of capacity considerations.

Figure 6: Resulting 19 Representative Traffic Peaks ordered by Cluster Size

Cluster number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Num. peaks	2839	2002	897	818	808	792	780	772	669	409	326	202	183	165	85	83	74	17	15
Num. airports	142	96	86	109	68	60	137	63	70	47	39	21	26	21	7	6	4	2	1

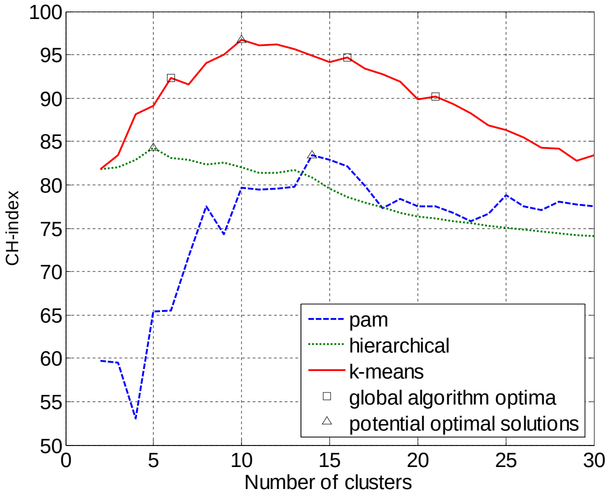


Duration [h]	2.4	2.6	2.5	2.8	2.8	2.5	6.9	2.6	2.8	3.1	2.6	2.5	2.7	2.6	3.6	2.6	2.4	5.0	3.8
Fill factor [%]	54	54	55	54	53	54	51	53	54	53	53	55	56	55	55	50	52	55	48
Rel. amplitude [%]	41	49	43	59	61	49	58	51	49	46	44	41	42	55	54	54	55	48	45

Notes: The peak traffic mix is provided by the bar graphs (for specification of aircraft weight classes see Figure 11 in Appendix), divided into arrivals (gray) and departures (white). The three additional shape-related parameters are listed below the bar graphs.

Application of the cluster analysis process to the airport-related data resulted in a global optimum index value for the CH-index for each of the three algorithms applied (see Figure 7). Highest overall index values were reached for k-means, hence the index graph of this algorithm was further investigated. Apart from the global optimum at 10 clusters, several local optima could be identified. Comparing the deviation of cluster median results from the original airport dataset resulted in 16 clusters being the overall optimal solution. Analyzing original traffic parameter deviations of individual airports from cluster median values indicated that the median of the absolute deviations in percent lies below 10 for medium jet aircraft and below 1 for heavy type aircraft.

Figure 7: Highest CH-index Values for Three Different Cluster Algorithms Plotted over the Number of Clusters



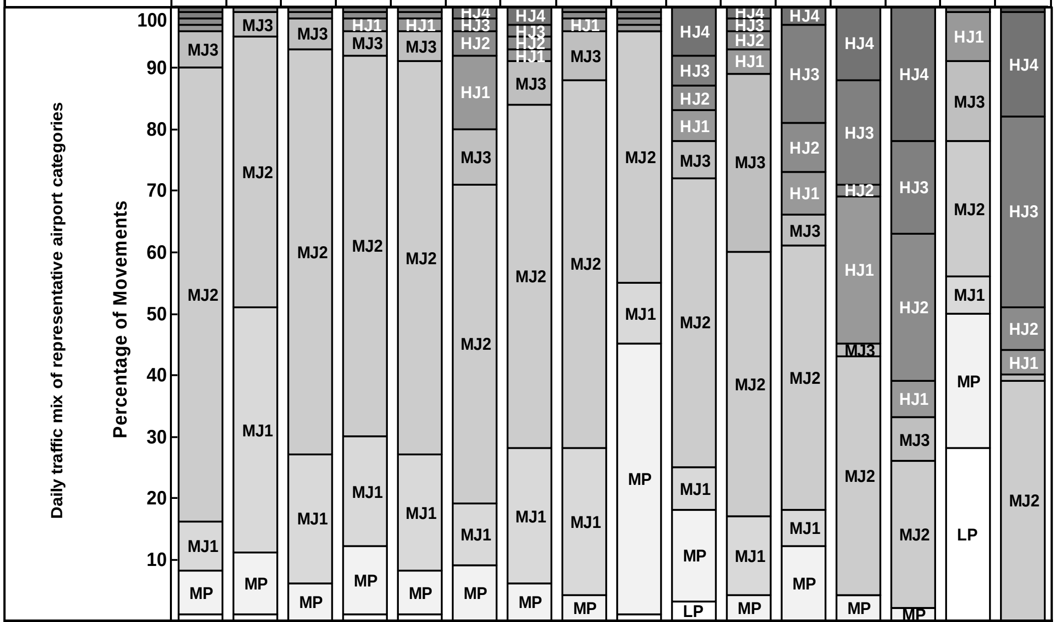
Notes: K-means shows highest values. Comparison and plausibility check of the global optimum (10 clusters) and local optima resulted in a final selection of 16 clusters.

The resulting representative airport categories for daily traffic mix and movement distribution related parameters are shown in Figure 8. The airport categories are ordered by the cluster size, which is specified by the number of airports considering seven days of the week.

It can be observed that airport categories of highest worldwide relevance are characterized by a high share of medium type aircraft. Category 1 contains primarily worldwide hub airports of different size, but also several origin and destination airports. Categories 2-5 contain a mix of different types of airports. Category 6 contains mainly hub airports, particularly in the Americas and Asia-Pacific region. Airport category 7 contains large hub airports that are characterized by a high traffic load throughout the whole day, such as Frankfurt or Chicago O'Hare. This is also reflected by the cluster result for the fill factor, which is highest for this category. Moreover, this category includes the highest share of worldwide large hub airports. The largest amount of smaller airports at touristic destinations as well as several origin and destination airports is contained in category 8, showing the lowest fill factor and a low relative load. In terms of night rest, category 10 contains several airports that allow considerable traffic during night hours (such as Dubai airport), resulting in the relative night rest of only 41%. Among the set of 16 categories there are also less representative ones in terms of cluster size (see right of Figure 8). Category 16, for instance, only contains seven days of the week of Singapore airport. However, this leads to a small share of JJ type aircraft in the traffic mix for this category. The largest share of light propeller aircraft has category 15, containing only a few different airports. Category 14 has the highest share of heavy aircraft traffic. It mainly contains four airports (for seven days a week) - ICN, TPE, HKG, AUH - which are large intercontinental hubs.

Figure 8: Resulting Representative Traffic-related Airport Categories Displayed in the Order of Cluster Size

Cluster number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Num. airports (7 days)	263	255	129	123	120	71	70	62	52	51	38	36	35	28	26	7



Total peaks	3	3	4	6	4	3	2	3	4	4	4	4	3	4	3	3
Arrival peaks	3	3	5	3	6	3	4	2	4	4	3	3	3	3	3	3
Departure peaks	3	3	5	3	2	3	3	2	4	2	3	3	2	2	2	2
Fill factor [%]	61	61	70	66	65	63	81	42	62	70	65	57	59	62	52	72
Relative load [%]	17	16	30	23	22	21	64	15	19	22	20	13	23	19	13	20
Rel. night rest [%]	88	87	80	92	90	89	76	101	94	41	86	99	99	80	100	46

Notes: 16 clusters were determined as the optimal solution for the combined cluster analysis of the daily traffic mix and movement distribution parameters. The bar graphs present the resulting daily traffic mix (a list of percentages is shown in Table 2 in the Appendix; for specification of aircraft weight classes see Figure 11 in Appendix). Movement distribution parameters are given in the table below the bar graphs.

The results for representative peaks and airports can now be combined. Therefore, first, the occurrence of a peak situation of an original airport in each of the representative peaks is counted for all airports analyzed. Then, peak occurrences are added for all airports in each representative airport category determined. Finally, the occurrence of representative peak types in each airport category can be provided in descending order of frequency. The highest three frequencies, hence, the most relevant peak situations for each airport category, are provided in Table 1.

Table 1: Most Relevant Peak Types in Representative Airport Categories

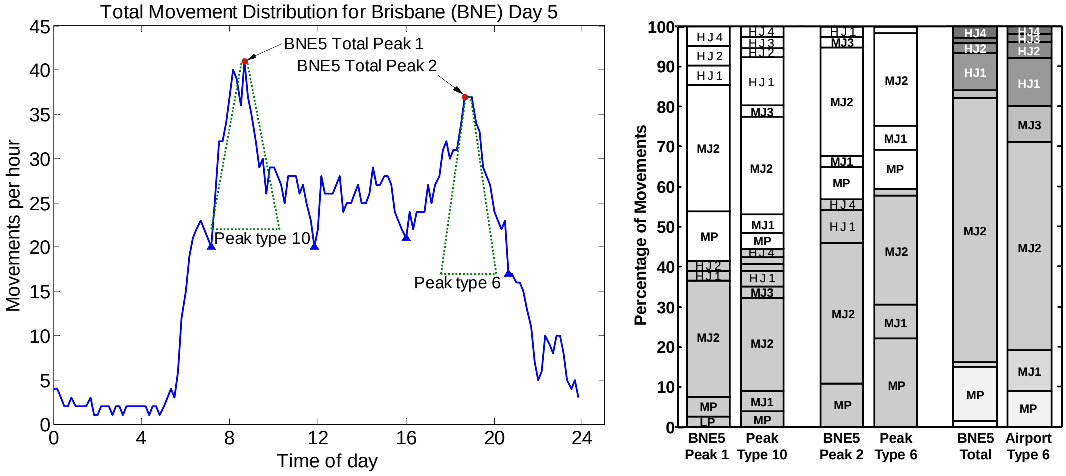
Representative Airport	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1st relevant peak	1	2	1	1	1	9	1	2	6	1	9	11	10	12	17	18
2nd relevant peak	4	5	2	6	2	10	2	5	8	13	3	14	11	13	16	19
3rd relevant peak	7	7	3	8	4	3	7	1	7	3	10	6	13	15	9	14

Notes: Only the three most relevant representative peak types (according to Figure 6) in representative airport categories of Figure 8 are shown, ordered by frequency of occurrence of peaks.

This list gives an indication of reasonable airport-peak combinations. However, it should be kept in mind that in Table 1 only the three peak types with highest frequency of occurrence for each category are listed and that, depending on the overall number of airports in a category, relevance of other peaks can still be significant. Especially for more representative categories containing many airports further peaks should be considered.

For a final demonstration of the quality of the representative categories of airports and peaks, a comparison is presented for one example airport (Brisbane BNE, day 5). Its daily movement distribution is shown in Figure 9 on the left, including two identified peaks. By comparing total absolute deviations of traffic mix percentages in the two peaks with all representative peaks of Figure 6, the closest peak type could be determined. A traffic mix comparison for both peaks is shown in Figure 9 on the right. It can be observed that arrival/departure ratios for both peaks are close to the original values. Representative values for duration, fill factor and relative amplitude were used to indicate the shape of both closest representative peaks (see dashed peaks in Figure 9). It can be observed that peak amplitudes are well met, while the representative peaks underestimate the original peak duration. Analyzing the total movement distribution, BNE airport on day 5 resulted in airport category 6 during the cluster process. Taking into account Table 1, peak types 9, 10 and 3 are most relevant for this type of airport, of which type 10 appears in the BNE example. As shown in Figure 9 on the right, the total airport traffic mix for airport type 6 is close to the original data for BNE. Movement distribution shape-related parameters for BNE are given in Figure 9 on left. Values are of similar order of magnitude compared to the representative airport type.

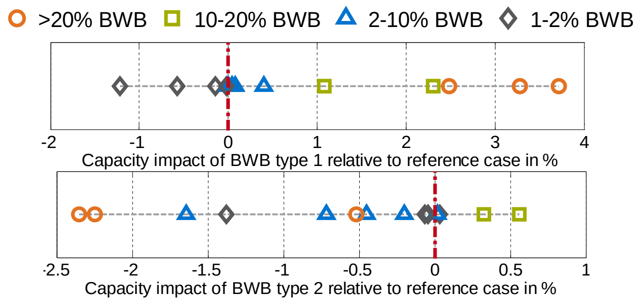
Figure 9: Airport Example Brisbane (BNE) compared to Representative Airport Category and Closest Representative Peak Types



Notes: The daily movement distribution and shape-related peak and airport features are shown on the left, the traffic mix structure is compared on the right.

The resulting representative airport and peak clusters can now be directly fed into runway capacity impact analysis. Each peak and airport cluster resembles a certain environment condition for which the capacity impact is determined. As a result, a range of impact values is determined, covering most relevant traffic situations worldwide. Figure 10 provides an exemplary result for the capacity impact range of two distinct blended-wing-body (BWB) aircraft evaluated with the 16 representative airport environments (for more detailed information on this example analysis refer to Öttl, 2013). The BWB aircraft substitute the aircraft weight classes HJ3+HJ4+JJ. Since not all airports contain these classes, only the ones where this aircraft type is present are shown. Capacity impact is described by the relative change in movements per hour possible at an airport when the aircraft type to be analyzed is present. The overall negative capacity impact of BWB type 2 can be observed compared to a rather positive impact of BWB type 1. This example demonstrates the importance of considering a variety of most relevant traffic conditions and not only a few local ones, as these environment conditions have a substantial influence on the results.

Figure 10: Exemplary Results for Capacity Impact Range of Two Blended-Wing-Body (BWB) Aircraft, Determined for the 16 Representative Airports



Notes: Based on Öttl (2013). Only representative airports as in Figure 8 are shown that contain this BWB aircraft type. The clear difference in impact can be observed.

5. CONCLUSIONS AND OUTLOOK

The main objective for this paper was to derive a systematic approach for specification of representative environment conditions of interest for technology impact evaluation on a global level. In particular, the airport traffic environment was considered, being of interest for runway capacity related evaluation studies. In general, impact evaluation is crucial for new technologies or concepts, as the planning and management of an efficient transport system requires detailed knowledge about the characteristics of this technology, including potential ranges of impact. The presented methodical approach based on cluster analysis ensures that the applicability of the respective technology is analyzed in a worldwide diversity of typical traffic situations.

Due to the variety of parameters of interest for different types of evaluations, it is not possible to derive one overall airport categorization that contains all relevant features of airport traffic. It is necessary to carefully specify the major traffic-related parameters of importance for the evaluation method and then find similarities in worldwide traffic situations to determine a representative set of airport categories. For the exemplary field of runway capacity evaluations a set of similarity parameters that describe the daily movement distribution were defined and their suitability investigated. Fill factor, relative load and relative night rest were selected as suitable to differentiate between distinct traffic features. Application of a systematic cluster-based assessment on traffic mix and movement distribution related parameters of 203 airports, analyzed for seven consecutive days, resulted in a set of 16 representative airport categories. This limited set of representative airports can serve as a standard input for capacity-related evaluations and ensure clarity and comparability on a technology level. By use of only a few representative types of airports, the worldwide diversity can be addressed and managed, without losing situations of importance. Additionally, 11936 traffic peak situations at airports were clustered according to their traffic structure and shape-related parameters, resulting in 19 representative categories. Each of the resulting representative airport categories could then be related to most relevant peak traffic situations.

Apart from the capacity example presented, this systematic approach to derive representative airport categories can also be applied to other fields. A further example for which traffic-related categories are needed is noise-related technology evaluation. Similar to the approach for capacity-related applications, similarity parameters of importance can be derived from the evaluation methods used. Considering the noise simulation software INM as an application example, the basic specification requirements include traffic on a daily basis, divided into day, evening and night time period, depending on the noise metric of interest (FAA, 2007). The share of movements for day, evening, and night time (according to EC, 2002), as well as the traffic mix structure for each period could be considered as potential similarity parameters in this context. Applicability of the presented approach is not only limited to traffic-related parameters. Similarities between any kind of entities or structures in air transport, such as airlines or air traffic control, can also be considered.

Taking only the current state of worldwide traffic into consideration to evaluate new technologies is a first step but not sufficient. Since new technologies are mainly introduced in future situations, a method has to be defined on how plausible future traffic situations can be determined. One possibility is to make use of scenario techniques to specify plausible future developments of environment conditions. The example presented in Öttl (2013) incorporates this type of approach.

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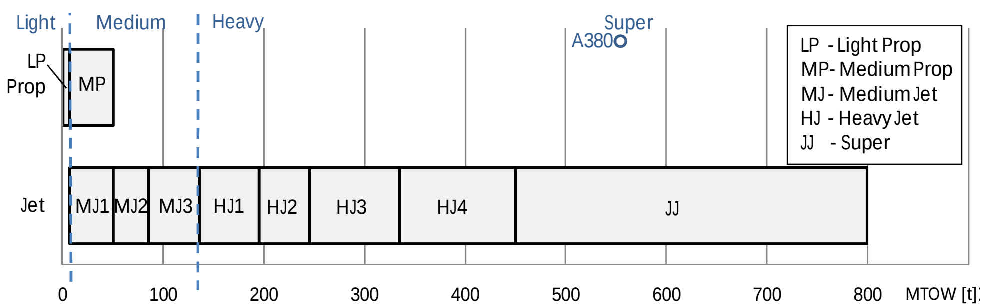
APPENDIX

Figure 11: Aircraft Weight Classes for Traffic Mix Parameterization



Notes: Derived from Öttl et al. (2013).

Table 2: Data Table for Traffic Mix Distributions of Representative Airport Categories in Figure 8

Represent. airport		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Daily traffic mix in % movements	LP	1	1	0	1	1	0	0	0	1	3	0	0	0	0	28	0
	MP	7	10	6	11	7	9	6	4	44	15	4	12	4	2	22	0
	MJ1	8	40	21	18	19	10	22	24	10	7	13	6	0	0	6	0
	MJ2	74	44	66	62	64	52	56	60	41	47	43	43	39	24	22	39
	MJ3	6	4	5	4	5	9	7	8	0	6	29	5	2	7	13	1
	HJ1	1	1	1	2	2	12	2	2	1	5	4	7	24	6	8	4
	HJ2	1	0	1	1	1	4	2	1	1	4	3	8	2	24	0	7
	HJ3	1	0	0	1	1	2	2	1	1	5	2	16	17	15	1	31
	HJ4	1	0	0	0	0	2	3	0	1	8	2	3	12	22	0	17
	JJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1