Influence and Sensitivities of Airport Capacity Limitations Modeling in Air Transport Fleet Development

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Post-pandemic air traffic development depends, among many other factors, on the availability of sufficient infrastructure. Airport capacities often constitute a bottleneck for further growth, while strategies for mitigating congestion might increase fuel burn and emissions. To quantify scenarios for infrastructure capacity effects on the air transport system, an approach integrating fleet development modeling, airport capacities, and strategies for congestion mitigation was set up. Within that approach, we investigate relevant calibration parameters for airport capacity modeling and show examples of the effects of changes to these parameters on air traffic and congestion. This paper describes generic methods for estimating airport utilization and growth potential. It also devises airport capacity growth factors, based on airport size, function, and region. The results obtained show the effect of these uncertain factors on the onset and spread of airport congestion. Further, they are consistent with the primary literature on the impact of capacity constraints on air traffic in Europe and Asia. Thus, this paper offers insights into major factors and potential pitfalls of airport capacity modeling, all within the context of a global fleet model.

Keywords: airport capacity limitations; airport congestion; air transport fleet development

I. Introduction

In the wake of the global COVID-19 crisis, the air traffic sector is expected to return to demand growth, although slightly below pre-pandemic projections [1,2]. This growth, however, is subject to many limiting factors: These include a lack of sufficient qualified personnel [3,4], aggravated by layoffs due to the pandemic, political and societal pressure resulting from the climate crisis [5], and the limited production capacities of aircraft manufacturers [6]. As outlined by previous reports, airport capacities also limit air traffic growth, see, e.g., [2] for Europe. Here, in a pre-pandemic high growth scenario, 16% of flights remain unaccommodated in 2040; with this being due to airport capacity shortages. However, there is considerable uncertainty about the significance of this limitation, especially in the aftermath of COVID-19. This is illustrated by [7], which reports that 12% of flights in a post-pandemic high growth scenario will remain unaccommodated, because of capacity limitations in 2050. This number is much lower for 2040, with almost no flights affected in a medium growth scenario. In contrast, a rate of 8% unaccommodated flights was observed in 2040 by [2] in a pre-pandemic medium growth scenario.

This paper contributes to a depiction of some of these uncertainties and identifies important influential parameters in modeling airport congestion effects on air traffic development. The presented approach is part of an integrated model which estimates the impact of airport congestion mitigation strategies as part of an overall assessment of novel aircraft designs. Starting with previous work and the basic modeling approach adopted in Section 2, Section 3 elaborates on a refined representation of airport infrastructure growth and on different use cases simulated for this work. Section 4 presents a discussion of the corresponding results. Section 5 gives starting points for future work and then concludes the paper.

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II. State of Affairs

The first part of this section gives a short overview of literature on the integration of airport capacity limitations into fleet development modeling. The second part details the approach followed for airport capacity estimation within the modeling framework used.

A. Airport Capacity Limitations within Fleet Modeling

Literature about the effects of airport capacity limitations mostly focuses on individual airports and the relevant implications on a local level. Ways of mitigating such restrictions are the subject of various research reports. Examples are the build-up of multi-hub systems [8,9] and an increase in average aircraft passenger capacity [10]. Analyses of the effects of airport capacities on global air traffic and fleet development are scarce in literature, however. One source for reference in this regard consists of the EUROCONTROL *Challenges of Growth* reports, which deal with this topic on a European level [2,7,11]. A short overview of these reports' findings was presented in the introduction. Further important research in this field was reported in [12] and, more recently in [13]. Here, possible strategies for mitigating airport congestion are also introduced. These strategies will simply be referred to as "mitigation strategies" below. Fleet assessments as part of the Clean Sky 2 Technology Evaluator project include airport capacity influences, which use different scenarios for technological development of aircraft and air traffic demand up to 2050. With larger aircraft deployed at congested airports as a mitigation strategy, significant airport capacity shortages lead to a growth in simulated average aircraft size [14]. These results suggest a considerable influence of airport congestion on future air traffic development and fleet mix; although the newest iteration of the EUROCONTROL forecasts has been more cautious in this regard [7].

Thus, airport capacities need to be considered in fleet development modeling. They also play an important role in the creation of requirements for the integrability of novel aircraft concepts into the air transport system [15]. Further, understanding the possible effects of mitigation strategies is vital for assessing the air transport network and operational levers that could be used to reduce emissions.

The integrated modeling approach of this work follows these findings. It is based on an evolutionary fleet development model (Fleet System Dynamics Model—FSDM), which was developed from previous research at the Technical University of Munich. This model estimates future fleet mixes and sizes, following a system dynamics-inspired approach. It does this by applying the Macro Approach to Fleet Planning (see [6] for a comprehensive description).

Within this model, different aircraft types and routes are clustered to reduce modeling complexity. Route clustering combines routes to route groups between six ATN (air transport network) regions. The biggest region, Asia, stretches roughly from the Urals in the West to Japan in the East, and from the Asian part of Russia in the north to New Zealand in the south. It thus comprises a set of economically very diverse countries. Different airlines are not modeled: All aircraft are assumed to be operated by a monopolistic airline. This model is used actively, e.g., for the holistic assessment of novel aircraft designs, such as fuel cell hybrid-electric aircraft [16]. The FSDM was recently included in an integrated model that estimated airport capacity utilization in parallel with fleet development [17]. This model was updated and improved in [18]. Its initial results are in a similar range to current work in the field [18]. This paper uses the updated integrated model. Herein, unaccommodated traffic due to capacity limitations ("surplus traffic") is calculated for each airport in each simulation year. In case surplus traffic occurs, two mitigation strategies are possible: usage of aircraft with larger passenger capacity or shifting of traffic to uncongested airports [19]. The thorough depiction of airport capacities and their development thus play a vital role with this modeling approach. This estimation of capacities and their influence on fleet model calculations are presented in more detail in the following section.

B. Generic Modeling of Airport Capacities

Airport capacities in the context of this work are understood as runway system capacity, since this usually constitutes the most critical bottleneck for airport traffic growth [12,19]. For global assessment within a fleet modeling approach, annual capacity values are required. This involves a considerable loss of modeling accuracy, as such factors as seasonality effects, traffic peak structures and aircraft operating sequences can only be approximated. Further, a generic method applicable to all airports has to be chosen. Thus, airport capacities are estimated analytically by a method proposed by Harris [20] and in a first iteration developed by Blumstein [21]. The calculation of practical hourly capacities under IFR conditions (PCIFR) is based on required time-based separations [22], including a time penalty added to all time separation values (as reported in [19]). After these absolute airport capacities are estimated, any kind of future capacity assessment requires knowledge about current capacity utilization and its development. Hub airports often see the first signs of congestion, once free slots are no longer available at peak hours. Thus, peak hours should be included in these considerations (see [23]). The corresponding calculation routine below is derived from [24] and mostly follows approaches from [12] and [23]. In contrast to the reports in [12] and [25], the global approach adopted in this work necessitates capacity utilization based on a single parameter only. The authors mentioned use both the capacity utilization index (CUI) and the 95% peak hour movements to evaluate airport congestion. The CUI is defined as the ratios of traffic volume during an average hour and of traffic volume during the 95% peak hour [12].

The basis for the following utilization calculation according to [24] is formed by OAG 2016 flight data [26]. It should be noted that this data disregards charter flights, for example. Thus, at some airports, capacity utilization is slightly underestimated. First, we calculate hourly capacity utilization CU_h for each operating hour of each airport in 2016:

$$CU_h = M_h / PCIFR. \tag{1}$$

M_h denotes the number of movements at the airport in that hour. Peak hour effects are included via a weighting factor G_h:

$$G_h = M_h / M_{d,6\text{-}22}. \tag{2}$$

In (2), $M_{d,6\text{-}22}$ is the number of movements over the entire day. This value considers only traffic between 6 a.m. and 10 p.m. (local time), as many airports are subject to night curfews. A consideration of night hours might therefore lead to an overly optimistic view of the capacity situation. However, for airports without night curfew and considerable nighttime traffic, this approach involves a conservative estimation of capacity reserves. Daily capacity utilization $CU_{d,6\text{-}22}$ is calculated as

$$CU_{d,6\text{-}22} = \sum(CU_h\ G_h). \tag{3}$$

To receive valid annual capacity utilization values, the 30th busiest day of the year was arbitrarily chosen as reference for each airport. Thus, events with unusually high or low traffic loads, such as holidays and off-season times, are not accounted for. The final model uses possible capacity growth per airport, CG, additionally taking into account an annual infrastructure growth factor GF:

$$CG = GF / CU_{d,6\text{-}22}. \tag{4}$$

The annual airport capacity growth factors account for airport expansion projects and operational improvements. They are obtained based on airport clustering, rather than on individual airports. Often, no exact growth projections for single airports are possible, e.g., regarding the completion date of airport expansion projects. In a global simulation environment, involving many simplifying assumptions, the additional effort for modeling future growth at individual airports would thus not be justified. A cluster-based approach still allows for considering different speeds of expansion of airports of different sizes and with differing network functions. Consequently, these two attributes were used to group all airports into six airport clusters (APC) (see [17]): Global Hubs (APC1) represent the largest airports with central Hub functions in the air traffic network. Large Airports (APC2) are usually secondary Hubs, while Medium Airports (APC3) often serve important urban centers without any Hub function. Long-haul Airports (APC4) are Medium- to Large Airports with a high proportion of long-haul services. Regional Airports (APC5) serve the O/D (origin/destination) traffic of smaller cities. The unnamed APC6 contains the majority of airports within the OAG 2016 data [26]. These are only served irregularly and play no significant role in terms of a global view of the air traffic network. The integrated model performs a clustering into these six APC in each simulation year, considering changes within the air traffic network over time. All airports are able to change cluster during the course of the simulation period. As described in the next section, this work adds a region-specific view of airport infrastructure growth to the APC.

III. Capacity Limitation Modeling and Use Cases

The integrated model used for this work is presented in more detail in [18]. Compared to a previous version [17], infrastructure modeling differs in two ways:

- Airport infrastructure grows with prescribed growth factors at all times – not just once an airport has already reached its capacity limit.
- Airport infrastructure growth factors are introduced on a region- and airport cluster-specific basis.

The latter refinement of airport infrastructure growth factors is described below before depicting the use cases for this work. These changes in modeling were already used by [18] for obtaining and describing global results. Similar to [17] and [18], effects of the COVID-19 pandemic are not considered. This simplifying assumption seems justified in view of the long-term time horizon covered by this work.

A. Airport Infrastructure Growth Factors

Preliminary assessment of the results presented by [17] showed a high number of Asian, especially secondary or tertiary Chinese, airports becoming prone to capacity shortages during the simulation period up to the year 2040. This was traced back to the infrastructure growth factors being used. These factors were specific to each airport cluster, taking into account different speeds with which airports of different sizes and network functions are expanded. However, these factors did not differ between regions, implying the same speed for airport extension, e.g., in Asia and Europe. The subsequent underestimation of expansion speed at Asian airports lead to the described capacity shortages; while European airports saw faster growth, as might be expected in reality.

To overcome this shortcoming, region-specific airport infrastructure growth factors are introduced in the present work. Due to airport capacity being defined in the current model as runway system capacity, data is required on extensions of the modeled airports' runway and exit taxiway systems. The timeframe for data collection was set to the years 2000-2016. All airports in APC1-5 (in total 1655 airports) were included in the data set. Airports in APC6 were expected to never experience capacity shortages, as they barely see any sizeable amount of traffic. 2016 OAG data [26] was taken as the basis for the airport clustering. The data used regarding airport extensions includes various web sources. Most importantly, this consists of the websites of relevant airports, data and descriptions from [27], and of the results of analyzing satellite images from [28]. This work presents a preliminary processing of this data, with a view to obtaining infrastructure growth factors: These account for the share of runways and parallel taxiways newly built in the selected time period. Further capacity calculations, e.g. consideration of the fleet mix operating at each airport, were out of scope to obtaining the annual infrastructure growth factors GF. These were calculated as

$$GF = ((n_{2000} + n_{new}) / n_{2000})^{0.0625} - 1. \quad (5)$$

In (5), n_{2000} is the number of runways at all relevant airports in the year 2000, n_{new} refers to new infrastructure completed until 2016 and the exponent to the 16-year timeframe. The new infrastructure includes independent parallel runways ($n_{parallel}$), dependent parallel or crossing runways (n_{cross}) and parallel taxiways (n_{taxi}) built between 2000 and 2016:

$$n_{new} = n_{parallel} + 0.7\ n_{cross} + 0.5\ n_{taxi}. \quad (6)$$

Thus, as can be seen in (6), new independent runways are treated as if a new single-runway airport was added to the system. The dependency of new dependent parallel or crossing/converging runways on traffic on existing runways is accounted for by a weighting factor of 0.7. New parallel taxiways were assumed to add the capacity of half a runway.

Table 1 depicts the distribution of airports across ATN regions and APC ($n_{airports}$). It shows the amount of new infrastructure elements sorted by the different aforementioned types and the resulting annual infrastructure growth factors.

Table 1 Airport infrastructure growth data.

APC1 – Global Hubs						
Region	$n_{airports}$	n_{2000}	$n_{parallel}$	$n_{cross.}$	n_{taxi}	***GF [%]***
AF[a]	-	-	-	-	-	0.00
AS[b]	12	20	10	4	-	3.14
EU[c]	7	20	4	-	-	1.15
LA[d]	-	-	-	-	-	0.00
ME[e]	2	3	1	-	-	1.81
NA[f]	9	42	1	2	-	0.35
APC2 – Large Airports						
Region	$n_{airports}$	n_{2000}	$n_{parallel}$	$n_{cross.}$	n_{taxi}	***GF [%]***
AF	2	4	-	-	-	0.00
AS	24	30	9	2	-	1.88
EU	26	51	4	1	-	0.55
LA	8	12	2	-	-	0.97
ME	3	6	-	-	-	0.00
NA	23	64	4	5	-	0.69
APC3 – Medium Airports						
Region	$n_{airports}$	n_{2000}	$n_{parallel}$	$n_{cross.}$	n_{taxi}	***GF [%]***
AF	24	28	1	-	1	0.33
AS	89	105	2	6	4	0.47
EU	74	102	2	-3	4	0.12
LA	36	47	-	-	-	0.00
ME	12	18	2	1	3	1.32
NA	45	89	3	-	-	0.21
APC4 – Long-Haul Airports						
Region	$n_{airports}$	n_{2000}	$n_{parallel}$	$n_{cross.}$	n_{taxi}	***GF [%]***
AF	13	17	-	1	-	0.25
AS	8	8	1	-	-	0.74
EU	5	8	-	-	-	0.00
LA	14	17	1	1	-	0.60
ME	2	1	2	-	-	7.11
NA	6	13	-	-	-	0.00
APC5 – Regional Airports						
Region	$n_{airports}$	n_{2000}	$n_{parallel}$	$n_{cross.}$	n_{taxi}	***GF [%]***
AF	79	87	3	2	0	0.31
AS	400	369	38	2	-14	0.53
EU	233	244	7	-	2	0.20
LA	188	197	3	-3	1	0.04
ME	30	31	4	2	1	1.09
NA	273	458	3	-3	2	0.03

a. Africa, b. Asia (incl. Oceania), c. Europe, d. Latin America, e. Middle East, f. North America

As can be seen in Table 1, Global Hubs and Large Airports in Asia experienced strong growth in the reference period (3.14 % and 1.88 % p.a., respectively). The total number of new runways in Asia is higher, than reported in [25], owing to substantial build-up of airport infrastructure at smaller APC3 and 5 airports; which are not considered in [25]. The same is true for most APCs in the Middle East, reflecting both the above average air traffic growth and the rapid development of these regions. In contrast, airport growth in saturated markets in Europe and North America was comparably small, with the numbers of new runways roughly corresponding to [25]. Special mention should be made of the negative values appearing in Table 1 for some infrastructure elements of APC3 in Europe and APC5 in Latin and North America. In these cases, dependent parallel or crossing runways were closed at some airports during runway layout restructuring. The reduction of 14 parallel taxiways noted for APC5 in Asia reflects a modeling assumption: Various new airports with a single (quasi-independent) runway were built in this region. These were added as new independent runways, however in 14 cases they do not feature a parallel taxiway, as generically assumed in the modeling approach. Thus, these non-existing taxiways had to be subtracted again from the capacity added.

B. Use Cases

The different use cases investigated in this work reflect some of the assumptions concerning central capacity simulation parameters. At the same time, they indicate the high level of uncertainty connected with these parameters. The following analyses are part of the initial model calibration efforts and yield significant insights into the effect of changing the most significant airport capacity-related parameters of the model. The following cases were considered for the simulation period 2016-2040:

case a) Basic case: includes the newly obtained region- and airport cluster-specific infrastructure growth factors and considers airport growth in every simulation year.

case b) Influence of the quality of airport capacity estimation: Case a) with a 10% reduction of input airport capacities in simulation start year.

case c) Influence of changes in infrastructure growth factors: 10% increase in infrastructure growth rate in Asia; no airport growth in Europe; otherwise like case b).

case d) Influence of changes in RPK (revenue passenger kilometers) growth factors: reduction on all routes containing Asia by 0.5 percentage points, otherwise like case c).

Use case b) considers the quality of the airport capacity estimation. As shown in Section II.B., this estimation is connected with certain assumptions and the results have to be interpreted accordingly. Indeed, it can be expected that the input values for airport capacities in 2016, as used in [17,18] and case a), represent an optimistic estimate. This is because congestion usually kicks in well below 100% capacity utilization other than as implemented here [14,29]. Assuming an arbitrary 10% reduction in these capacities thus appears to be a valid assumption.

The changes in case c) reflect the uncertainty of future infrastructure development after 2016. While the change in infrastructure growth factors is chosen arbitrarily, it still covers the specific trends in airport expansion in Europe and Asia. A review of such recent airport expansion measures, which are not considered in Table 1, shows significant differences between both regions. This review uses similar sources to those in Section III.A, especially [27] and [28]. In Europe, there is only one current project concerning APC1: the opening of the new Istanbul airport (IST, five runways), replacing Atatürk airport (three runways). In APC2 there are currently two parallel runways under construction (DME and SAW). One parallel runway was opened in 2019 at SVO. DUB changed its runway layout in 2022, while BER replaced TXL and SXF in 2020.

At the same time, in Asia, within APC1, new runways were already introduced in CGK (2019), ICN (2021), and HKG (2022). Five further airports are currently undergoing the addition of a new runway (BKK, CAN, DEL, PVG and SIN). Beijing received an additional airport with four runways (PKX) in 2019. Only three airports are currently not undergoing expansion of their runway system (HND, KUL and SYD). Regarding APC2, BNE saw a change of its runway layout in 2020 and CKG and HAK have received new runways since 2017. New runways are under construction at four airports (CGO, CSX, KMG and XIY). A new airport was added in Chengdu (TFU) and new airports are under construction in Manila, Ho Chi Minh City, and Xiamen. Thus, in Europe, no significant increase in runway capacity can be expected in APC1 and 2 in upcoming years. Existing expansion projects center on the airports of Moscow and Istanbul. In contrast, most Asian airports will undergo further expansion, with new airports being added to the network. This supports the trends shown by the changes made in use case c); although admitting that the no-growth assumption for Europe represents a worst-case scenario.

Case d) shows, by way of example, the influence of small deviations in demand growth. Changes to the Asian region were chosen, since it is one of the most important ATN regions and experiences the greatest congestion effects of any ATN region.

IV. Results and Discussion

This section presents the simulation results for the use cases; first, on a global scale in the form of RPK development, and then, in a more detailed regional view of congested airports and congestion events. The second part of the section discusses the results so obtained, while also taking into account those at airport level. A plausibility check of the results is not presented, as these follow the results and plausibility considerations in [18]; with use case a) being similar to the "use case" in [18].

A. Results of the Use Cases

Figure 1 presents the development of global RPK in the simulation period. Use cases a), b) and c) achieve almost similar RPK growth in this period. With each successive use case, more capacity restrictions are introduced. Thus, a growth in surplus movements can be expected. The overall results in Fig. 1, however, show that the deployed mitigation strategies effectively counter the congestion created. Consequently, the RPK levels of cases b) and c) are well below one percent lower in 2040 than in case a). Case d) behaves in a similar way, where lower traffic growth in Asia is the reason for a 4 % lower RPK value in 2040, as compared to case a).

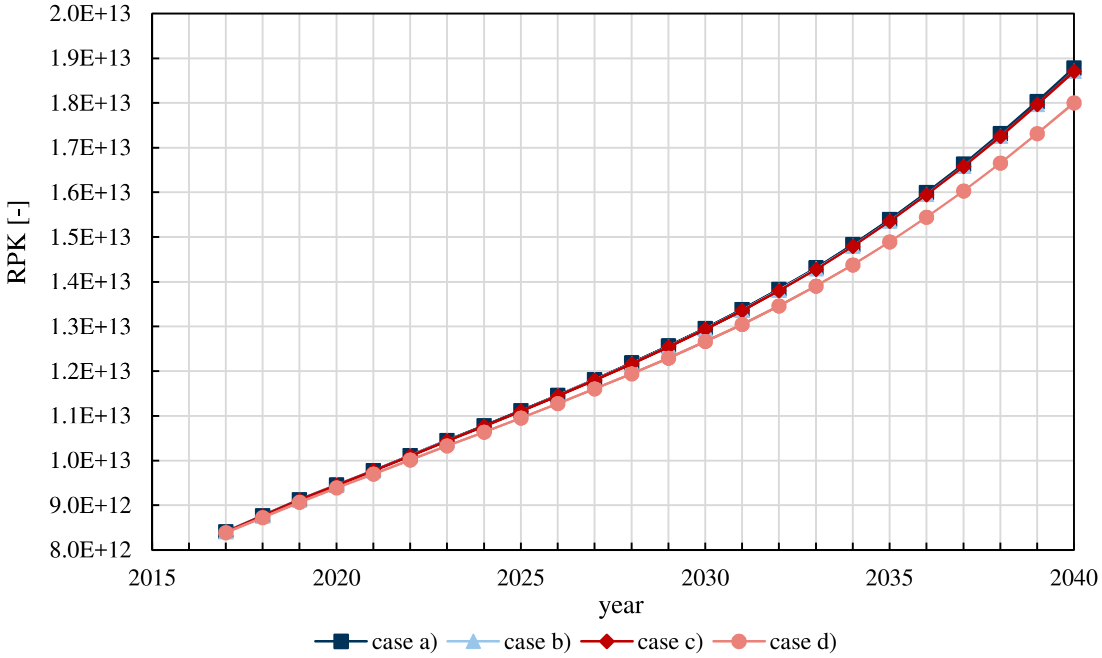

Fig. 1 Simulated development of global RPK for the four use cases, 2017-2040.

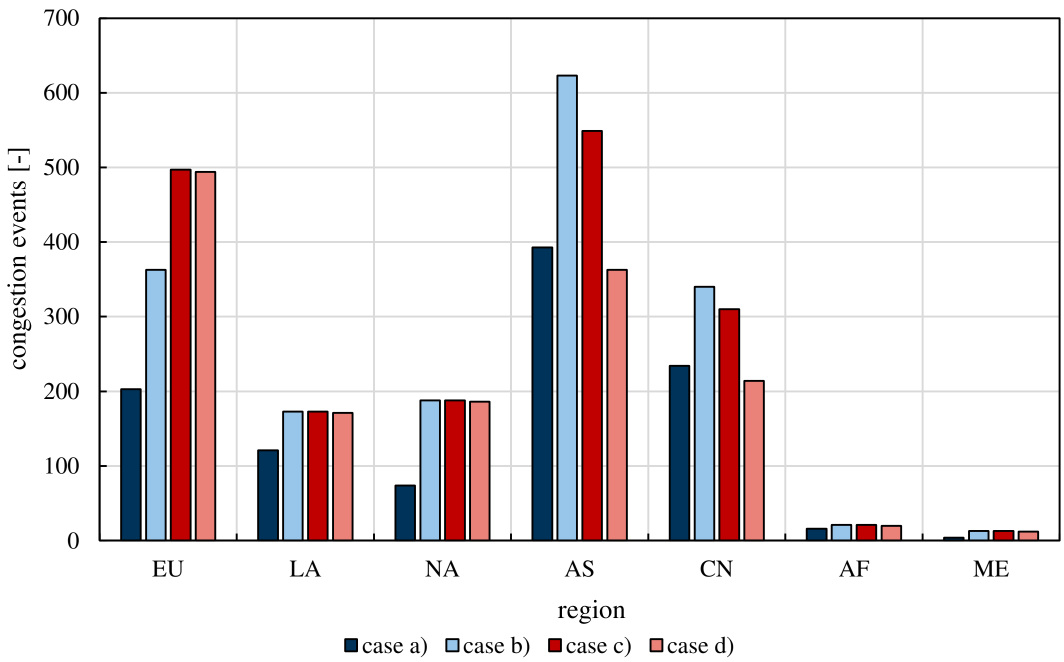

Fig. 2 Number of congestion events in the simulated regions for the four use cases.

Figure 2 depicts the number of congestion events in the simulation period for each of the six regions. A congestion event is defined as an airport experiencing surplus traffic in one simulation year. An individual airport can have multiple congestion events, if it is congested in multiple simulation years. Within the modeling assumptions, an airport congested in one year will most likely be congested in all subsequent years, as traffic and infrastructure growth factors are assumed to be constant throughout the simulation period. Figure 2 reveals that Asia and Europe experience the highest numbers of congestion events. Except for case d), Asia has most congestion events. Despite the lower demand growth in Asia in case d), the highest number of congested airports is to be found in this region in all cases. China (CN) alone, as part of the Asian ATN, experiences more congestion than either North or Latin America. Both of the latter, however, still experience significant airport capacity limitations. All other regions show limited congestion at individual airports (Africa: JNB and DUR, Middle East: DXB). Consequently, the number of airports congested in the simulation period follows the same trends, as can be seen in Fig. 2.

Table 2 presents the number of congested airports for every simulation year in the ATN regions most affected by congestion—Asia (AS) and Europe (EU). For more detail on the Asian ATN region, the number of congested airports located in China is shown, too.

Table 2 Numbers of congested airports in Asia (AS), China (CN) and Europe (EU) during the simulation period.

Year	case a)			case b)			case c)			case d)		
	AS	*CN*	*EU*	*AS*	*CN*	*EU*	*AS*	*CN*	*EU*	*AS*	*CN*	*EU*
2017			1			1			2			2
2018			1			2			2			2
2019			1			2			2			2
2020			1	1	1	1			5			5
2021			1	3	2	3	2	1	7			7
2022			1	3	2	3	3	2	7	2	1	7
2023			1	3	2	5	3	2	8	2	1	8
2024			1	5	4	6	5	4	11	3	2	11
2025	1		1	6	5	7	5	4	13	3	2	13
2026	2	1	2	10	7	7	8	6	16	4	3	16
2027	2	1	2	12	8	9	10	7	17	5	4	17
2028	5	4	4	16	11	11	13	8	20	8	6	19
2029	9	6	6	19	11	13	15	10	23	9	6	23
2030	9	6	6	23	14	15	20	12	23	11	7	23
2031	14	8	9	27	16	17	21	13	23	12	7	23
2032	19	12	9	33	18	19	27	16	23	13	8	23
2033	25	16	10	38	22	23	34	20	25	20	11	25
2034	29	17	14	44	26	25	38	23	25	23	13	25
2035	33	20	17	53	29	25	43	26	32	29	16	32
2036	38	24	18	56	29	26	49	27	35	35	21	34
2037	43	27	20	58	30	30	55	30	42	38	23	41
2038	50	29	24	64	31	32	58	30	43	45	27	43
2039	55	31	25	70	35	38	66	33	44	48	27	45
2040	59	32	28	79	37	43	74	36	49	53	29	48

Both Fig. 2 and Table 2 lead to the following observations: All use cases have in common that most congested airports are located in Asia (especially China), followed by Europe. Comparing case b) with case a), we observe an earlier onset and greater extent of congestion. Europe sees a rapid increase in congestion, almost doubling the number of affected airports. A peculiarity in case b) is the decrease in congested airports in Europe between 2019 and 2020. This is due to LHR, the first congested airport in Europe, not reaching its capacity limits between 2020 and 2031. A reason for this unexpected behavior could not be found to date. Case c) sees a slight reduction in congestion at Asian airports, while further aggravating the situation in Europe, however. In case d), a significant reduction in congestion events in Asia is achieved, while Europe has only one congested airport less than in case c). This relates to changes in the global distribution of new aircraft and subsequent changes, also, of the intra-European fleet mix following the slower growth in Asia. The results shown in this section yield starting points for comparison with findings in the literature and for further discussion below.

B. Discussion

The above results show important effects of the changes introduced with each successive use case. The overall RPK development in Fig. 1 follows the values for congested cases reported in [18]. RPK growth in this work was the same as in the previous study and in a range similar to that reported in [1]. The share of unaccommodated RPK in 2040 is below the one described in [14]. Two of the reasons for this deviation are the different modeling approaches adopted and the more effective congestion mitigation employed. The number of congested airports is well above the literature findings, which indicates a wider spread of congestion [18]: In 2050, 24 to 36 airports are expected to be congested in [14]. In this work, 119 (case a)) to 165 (case c)) airports become congested by 2040. In [25], 119 airports are investigated in terms of their tendency for congestion. Most of them experience congestion in our model, too.

Considering the changes made in the different use cases, the reduction in initial airport capacity by 10 % seems to have the most significant effect, increasing the number of global congestion events by 70 % alone. The increase in infrastructure growth factors in Asia in case c) led to a reduction in this region's congestion events by 12 %, compared to case b). At the same time, neglecting airport capacity growth in Europe increased the number of congestion events there by 37 % and globally by about 4 %. The reduction of RPK demand growth in Asia in case d) virtually only influences on this region, where it delays the onset, and reduces the spread, of congestion. Congestion events in Asia are reduced by 39 %, leading to a global reduction of about 14 %, when compared to case c). The significant global effect again underlines the importance of the Asian ATN in general. Thus, below, the basic issues are shown, by way of example, for the two major, yet very different, ATN regions of Europe and Asia. Developments in other regions are described briefly at the end of the section.

The onset of sustained congestion appears in the first simulation years at LHR and MEX. In cases c) and d), these are joined by IST. Interestingly, congestion in Asia sets in late in all use cases, starting earliest in 2020 at HKG in the most limited use case b). In contrast to these results, the literature suggests that there is already congestion at various airports around the world (see [25] or [30]). This hints at an underestimation of current airport capacity utilization. A general trend of decreasing ability to accommodate RPK demand, together with increasing limitations in airport capacity, can be observed in Fig. 2; comparing use cases a), b), and c). The development in case c) reflects the delayed onset of capacity shortages in Asia, owing to higher infrastructure growth factors. At the same time, congestion at European airports builds up earlier than in case b), with ten additional airports congested in 2029. Afterwards, however, Europe does not experience a significant rise in congestion events, compared to case b): The number of congested European airports in 2040 increases slightly from 43 to 49 (Fig. 2). This indicates that the set of airports prone to congestion in Europe is limited mostly to those airports already congested in case b). Table 3 further supports this observation. It shows (in case c), using 2016 airport clustering) that a majority (57 %) of congested airports in Europe are either Large or Global Hub Airports. A further 41 % is accounted for by APC3 airports, which leaves one additional APC5 airport (LIN). This also indicates a somewhat centralized traffic network, dependent on Hub airports. Still, the difference in the number of congested airports in Europe between cases a) and b) clearly shows the sensitivity of the European airport network to congestion. In general, European airports identified as congested in this work are notorious for their capacity shortages. Airports, such as LHR, IST (Atatürk) and FRA, are often described as congested in the literature [23,25].

As mentioned, Asia is the region by far the most affected by congestion. As in Europe, further reductions in available capacity in case b) led to a significant rise in the number of congested airports. However, the set of airports affected by capacity shortages in Asia is much less limited than in Europe. This can be seen by comparing Tables 3 and 4 for case c). Hub airports of 2016 APC1 and 2 account for less than half of the airports congested in 2040 (42 %). However, 51 % of congested airports are part of APC3, and a further four airports are regional APC5 airports. The reasons for this are manifold: First, the average number of runways per airport is significantly lower than for the respective airport clusters in Europe. For Global Hubs we observe, on average, 3.43 and 2.83 runways per airport in Europe and Asia, respectively. Large Airports have, on average, 2.15 runways per airport in Europe and 1.67 runways per airport in Asia, while at Medium Airports there are 1.36 and 1.27 runways per airport in Europe and Asia, respectively. While a significant expansion of airports in these clusters in Asia has taken place already, comparison with European airports shows that there is still some potential for further expansion. The examples in Section III.B show that this need for adaptation to rapidly rising demand is acknowledged, especially in China, which accounts for both the majority of congested airports and expansion projects.

Table 3 Total airports and congested airports in Europe, their number of runways and expansion projects (2000-2016), case c).

APC[a] (2016)	airports		expansions		runways	
	total	*congested*	*total*	*congested*	*total*	*congested*
1	7	7	3	3	3.43	3.43
2	26	21	5	4	2.15	2.19
3	74	20	8	3	1.36	1.60
4	5	-	-	-	1.60	-
5	233	1	18	-	1.08	1.00

a. according to Table 1

Second, shifting traffic from congested larger airports to smaller APC3 airports might accelerate the congestion of these airports, as illustrated in [18] for MEX. The congested airports in APC3 usually have only one runway each. This means that considerable growth was possible in the past, because the necessary runway was available from the start of operations. With the current strong growth in demand, however, the capacity limit for this single-runway system might be reached for the first time. This would necessitate a jump toward a dual-runway system. Moreover, some secondary cities in China saw rapid air traffic growth and airport expansion as part of local government efforts to boost economic growth, often in competition with neighboring regions. This issue is described in [31] by analyzing two such example airports, with one even setting explicit goals for competition with a Global Hub airport.

Table 4 Total airports and congested airports in Asia, their number of runways and expansion projects (2000-2016), case c).

APC[a] (2016)	airports		expansions		runways	
	total	*congested*	*total*	*congested*	*total*	*congested*
1	12	11	12	11	2.83	2.91
2	24	20	11	9	1.67	1.75
3	89	38	12	6	1.27	1.29
4	8	1	1	1	1.13	2.00
5	400	4	54	-	1.02	1.00

a. according to Table 1

In both investigated regions, all Hubs in APC1 (except for BKK in Asia) and almost all airports in APC2 are congested by 2040. On the one hand, this clearly follows the expectation that Hubs usually have a higher utilization rate and, thus, congestion starts at these airports. The lack of significant differences in the comparison of average runway numbers per total and per congested airport in Tables 3 and 4 supports this hypothesis: While, as seen above, the number of runways per airport has an influence on the onset of congestion, more decisive factors are airport size and function, as well as a region's traffic development. On the other hand, the results for Asia indicate that the relatively high growth rate of Asian airports in APC1 (3.14 % p.a.), which is due to past expansion projects, is still not sufficient to cover long-term growth. HKG is one of the four airports in this cluster with only two runways at the start of the simulation. Given a high initial utilization rate, it might be the first airport where congestion events are to be expected in the real world. This is shown in [32], which is similar to the findings of the integrated model. Interestingly, all four of these airports (BKK, CGK, HKG, and SIN) are currently undergoing expansion to a system of three parallel runways; as local governments compete for hub traffic in South-East Asia [32]. Similarly, the high number of congested Asian airports in APC2, which already underwent expansion before 2016 (nine airports), strongly suggests that air traffic growth in Asia exceeds the corresponding expansions in infrastructure. This is in line with [25], which mainly identifies airports in Asia, especially in China; where "expansion provided only a temporary relief from congestion."

Finally, the results for Asia reveal a further weak point in current modeling. Besides the expected capacity issues at airports in fast-growing markets, many airports in saturated air traffic markets experienced congestion events. This concerns mainly airports in Japan (nine airports in case c)) as well as in Australia and New Zealand (five airports). In fact, one of the first two Asian airports affected by congestion in all use cases is Fukuoka (FUK) in Japan. The problem in this regard is that, even for these saturated markets, the high RPK growth factors for the entire Asian region currently apply. These overestimate air traffic growth in these countries. Further, the above-described airport extension projects in China have led to infrastructure growth factors considerably higher than those of other fast-growing markets; e.g. Vietnam and India. These factors are also used with saturated markets but cannot balance out strong demand growth. Disregarding these developments might lead to a significant overestimation of capacity constraints and congestion in certain parts of Asia.

So far, we only investigated the APC as of the simulation start year. Yet, the airport clustering is updated in each simulation year within the integrated model. The development of the cluster classification of congested airports gives insights into general network developments in the various ATN regions, as shown below for Europe and Asia in use case c).

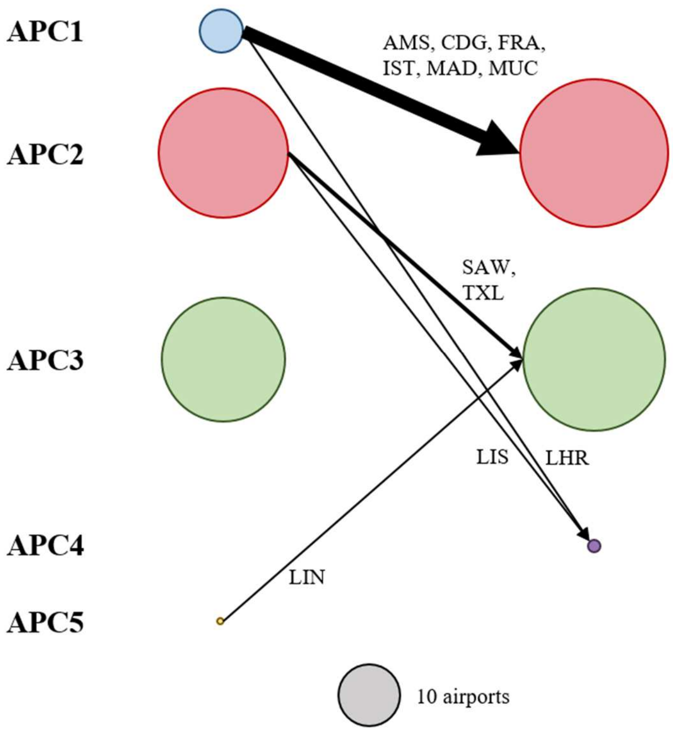

Fig. 3 Congested airports per APC (to scale) and APC changes in Europe, 2016 (left) to 2040 (right).

Figure 3 shows the division of airports in Europe congested in 2040 into APC as of 2016 (left) and 2040 (right). The diameter of the circles scales with the number of airports. Further, airports changing the APC during the simulation period are indicated by arrows (thickness scales with number of airports). In the 2040 clustering, there is no APC1 airport left in EU, with six of the former seven Global Hubs now being part of the "smaller" APC2 cluster. This indicates the decreasing importance of the European ATN, especially as compared to Asia. In 2040, APC1 airports can mostly be found in the latter region. As European airports experience low traffic growth, they lag behind in traffic numbers in the global comparison used for airport clustering; and they leave their APC1 "status" to airports where demand grows much faster. Curiously, the largest European airport by passenger numbers, LHR, changes to APC4 (Long-haul Airports). The reason for that is the exceptionally high share of long range flights at this intercontinental Hub [18]. Thus, in 2040 airport congestion in Europe takes place mostly in APC2 and 3.

Similar to Fig. 3, Fig. 4 shows the division of airports congested in 2040 in Asia into APC as of 2016 (left) and 2040 (right). Again, the high amount of congested APC3 airports becomes apparent. Unlike Europe, the amount of congested airports classified as Global Hubs in 2040 is higher than using the 2016 clustering. At the same time, using the 2040 clustering, the share of APC3 airports among the congested airports increases, as three airports classified as Regional Airports (APC5) in 2016 have moved up the hierarchy to APC3. Further, three former APC2 airports have decreased in importance and become APC3 airports as well. Thus, in the 2040 clustering, fewer congested airports are part of APC2, which indicates a general decrease in importance of this cluster. At the same time, owing to high traffic growth, more Asian airports move up to Global Hub status, while other Hubs operate within more regional networks, attracting a classification as Medium Airports.

As seen in Table 2, airport congestion does not play a major role in Africa or the Middle East. In Latin and North America, however, it reaches significant levels, despite being lower than in Asia and Europe. In North America, congestion mainly concerns the currently largest Hubs, which are part of APC1 and 2. Interestingly, these airports have extensive runway systems; with 4.88 runways per congested APC1 airport and 3.00 runways per congested APC2 airport (2016 airport clustering). This supports the above hypothesis that especially the functional parameters (traffic volume and network function) of an airport determine whether it is prone to congestion or not. Interestingly, most congested airports classified as Global Hubs in 2016 lost this status by 2040. This resulted from both the rising importance of Hub airports in Asia and from minor traffic and infrastructure growth factors in North America.

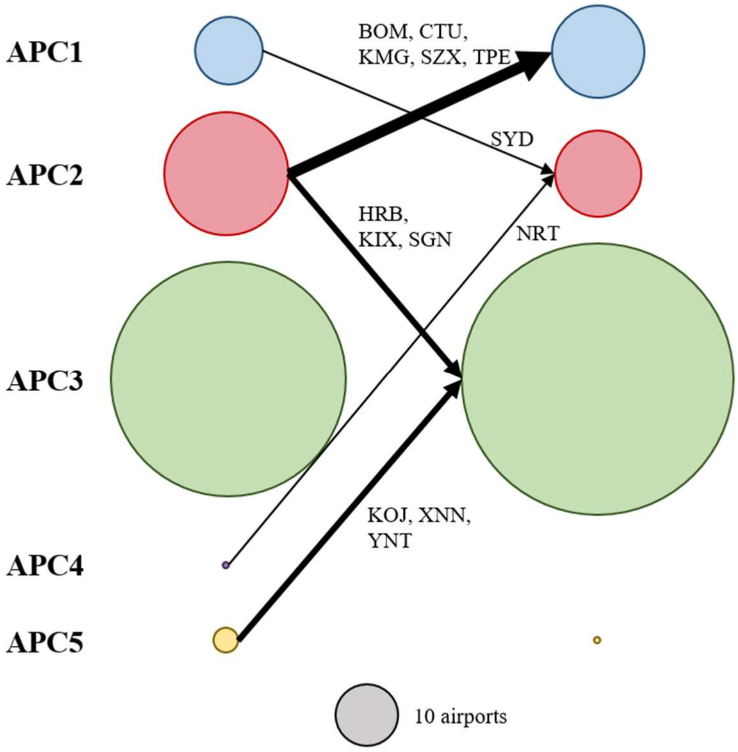

Fig. 4 Congested airports per APC (to scale) and APC changes in Asia, 2016 (left) to 2040 (right).

There are no APC1 airports in Latin America, since overall traffic levels there are too low, when viewed on a global scale. Thus, congestion mainly concerns APC2 and 3 airports. Further, owing to high traffic growth, congestion is spread more widely across the network; with five APC5 and even one small APC6 airport becoming congested. This corresponds with the literature about "the lack of an adequate infrastructure" [33] in this ATN region. Latin America likewise sees a variety of ways to incorporate congestion mitigation within our modeling: While some airports are able to shift high shares of surplus traffic to other airports (MEX in [18]), congested airports in Brazil, especially, lack uncongested alternatives. These airports have to rely solely on the deployment of larger passenger capacity aircraft. Congested airports in Latin America rarely change their APC throughout the simulation period.

V. Future Work and Conclusion

This paper presents insights into calibration work for the integration of airport congestion modeling into an evolutionary fleet development model. Changes to input airport capacity utilizations for the simulation start year, as well as infrastructure and demand growth factors, were investigated. The regions most prone to future airport congestion, according to the modeling results, are Asia and Europe, as reported in the available literature. In Europe, congestion was shown to affect mainly the largest airports. In Asia many airports in the second tier become prone to capacity shortages, too. According to the results, the high level of investment in infrastructure development currently undertaken in Asia might still not be sufficient to cope with capacity limitations entirely. In all simulated cases, the implemented congestion mitigation strategies almost completely prevent unaccommodated demand. Only in the final simulation years does congestion reach levels too high for mitigating all capacity constraints; which in turn leads to minimal remaining surplus [18].

The differences in air traffic and infrastructure growth within Asia, which are disregarded in this work, point to the necessity of a further breakdown of this modeling region into different subregions. Furthermore, the derivation of infrastructure growth factors can be improved: First, airports were considered for the cluster they were part of in 2016. For a more exact modeling, possible cluster changes of these airports between 2000 and 2016 should be accounted for. Second, the intuitive approximation of capacity improvement due to expansion projects should be replaced by the use of more precise analytical calculations: for example, taking into account the actual fleet mix at the respective airports. Still, as future airport expansion projects and their finalization date are usually unknown, any growth factor is subject to some inherent uncertainty. The underestimation of airport capacity utilization at simulation start implies changes to the calculation of this factor. In the same way as other authors, for example, use a CUI of 0.7 as threshold for congestion [29], different possible values for such thresholds should be tested for the above-presented CG value. In any case, this observation is in line with the issues mentioned in designing use case b) in Section III.B.

Despite these shortcomings, the infrastructure capacity growth factors presented here on an airport cluster and regional basis add both greater accuracy and greater latitude to the described integrated approach of fleet development modeling. The latter involves airport capacity limitations and their mitigation. They also allow for superior calibration of both the calculation procedure and the results described in this work. Despite the global modeling approach, however, it was still possible to show that regional results for individual airport clusters, and often for individual airports themselves, are both predictable and explainable. In turn, the integrated model's estimates thus appear to be correspondingly more accurate, traceable and explainable. This constitutes an important step in estimating the influence of infrastructure capacities on fleet and emission developments. Ultimately, in this context, the groundwork has also now been laid for better modeling of the operational levers that could be used to reduce aviation emissions.

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