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Ratio-based design hour determination for airport passenger terminal facilities

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ABSTRACT

To avoid both over-design and under-sizing of airport passenger terminal facilities such as security checkpoints, the infrastructure is designed for a specifically determined design load. As such, the design load is considered for a short period of time, usually an hour of operation, during which peak, though not necessarily maximum, demand occurs. For strategic planning applications, future design loads can be determined by either fictitious flight schedules or ratio-based models which forecast the relationship between design load and annual demand. This study presents two ratio-based methods which allow the direct determination of design hour loads (DHL) for passenger terminal facilities. The unsaturated DHL model considers the relationship between observed passenger flows in the terminal and aggregated annual demand data. The saturated DHL model includes several operational constraints which limit the actual DHL, such as limitations in the runway system or the fleet mix operating at an airport. Both models are applied to two real-world airports, for which the DHL of the security checkpoint facilities is estimated from large datasets covering multiple years. Results are significant at the 5 % level and suggest that the proposed ratio-based methods are appropriate for airport strategic planning applications.

1. Introduction

An integral part of airport strategic planning is the definition of facility requirements which are based on the systematic description and quantification of capacity shortfalls that result from the imbalance between future levels of supply and demand for airport facilities (FAA 2015; FAA 2018; IATA 2017; ICAO 1987). While the provision of capacity is usually specified with an inventory comprising of a list of currently operational and available infrastructure (IATA 2017), forecasting future demand levels presents more complex challenges for airport managers, consultants or planners. For airport strategic planning, where time horizons can extend from 20 to 50 years, aggregated demand forecasts are used; these estimate future annual traffic levels, such as total passengers per year or air traffic movements (ATM) per year. While aggregated demand data can be useful for the planning of facility requirements of certain airport facilities, such as stands and gates, as well as the preliminary sizing of the required floor space for passenger terminals, the sizing of specific facilities, such as check-in, security checkpoints, etc., requires the availability of *design load* forecasts (IATA 2017). As the term implies, design load describes the anticipated demand levels for short periods of time. These time periods are determined in such a way that infrastructure is designed with sufficient capacity to process demand at a defined level of service throughout the year, avoiding the risk of over-design in the few instances when extreme peaks may occur (De Neufville, Odoni, Belobaba and Reynolds, 2013). Depending on the type of facility for which requirements should be defined, design loads are either specified for a day, an hour, or even shorter intervals (Kennon et al., 2013). Interestingly, there is no standard method to determine design load that is universally accepted by researchers and practitioners (Ashford, 1988). Often, the selection of a specific method depends on the individual preferences of the airport operator, authorities and other stakeholders.

In fact, to determine facility requirements of passenger terminal facilities, a design hour load (DHL), which is the aggregated demand over the period of the design hour, is normally used (IATA 2017; Tošić, 1992). A number of different definitions for DHL exist in the literature

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(De Neufville et al., 2013; FAA 2018; IATA 2017; ICAO 1987; Kennon et al., 2013; Kincaid et al., 2012). Definitions which are widely used are the *standard busy rate* (SBR), the *busy hour rate* (BHR), or the *typical peak hour passengers* (TPHP). The SBR is defined as the "30th highest hour of passenger flow", which is "the flow that is surpassed by only 29 h of operations" for the entire year (Ashford et al., 1997, p. 30). The BHR is the "busiest hour for which the cumulative hourly traffic exceeds 5 per cent of the annual traffic" (Psaraki-Kalouptsidi, 2010, p. 141), and the TPHP is defined as "the peak hour of the average peak day of the peak month" (Ashford et al., 1997, p. 34). Given these different definitions of DHL, practitioners are recommended to select an appropriate measure with care. Indeed, research indicates that, for instance, the BHR is a more robust measure than the SBR, since "the percentages of passenger encountering flow rates greater than the SBR can easily vary from under 2 % at large airports to over 10 % at smaller ones" (Matthews, 1995, p. 58).

To empirically determine DHL, either the *design day schedule method* or the *ratio method* can be used. While the former is based on the definition of future design day flight schedules, the latter is an empirical data-driven method which aims to model the relationship between the DHL and annual demand by means of constant ratios or regression models. In the simplest case, this relationship is assumed to be constant. However, at capacity constrained airports, where the maximum number of annual ATM is limited due to operational, political, environmental or legal reasons, the relationship between DHL and annual demand becomes increasingly non-linear, the more closely an airport operates at its maximum capacity. In the literature this is referred to as *capacity saturation* (De Neufville et al., 2013; Kennon et al., 2013).

The ratio method is well documented in the literature and has found widespread application in airport strategic planning, where it is predominantly used to define overall DHL, which is the DHL of all departing, arriving or transit passengers in a passenger terminal. However, the ratio method has yet to be applied to determine DHLs for specific airport passenger terminal facilities, e.g., check-in facilities, the security checkpoints, the border control facilities, etc. This gap in the literature most probably relates to the lack of datasets which systematically describe passenger demand by means of a time series of observed passenger flows in facilities over multiple years (Raff and Wicki, 2019). In recent years, airport operators have increasingly been accumulating and storing large volumes of data generated by automated passenger tracking systems (PTS). These measure (i) passenger influx and outflux at facilities with boarding pass readers, turnstiles, or light barriers, and (ii) movement of passengers captured by camera or by tracking the Bluetooth or Wi-Fi-signal of cell phones. While PTS are predominantly used for operational purposes (e.g., management of queues, delays, scheduling of staff, etc.), the generated datasets which systematically describe passenger flows in terminals and at the various terminal facilities in particular could just as well be applied to strategic airport planning. Consequently, the objectives of this paper are firstly to utilize PTS datasets for the parametrisation of a ratio-based model which is capable of describing the relationship between aggregated annual demand levels and DHLs for specific passenger terminal facilities, secondly to incorporate saturation effects of capacity constrained airports into this model, and thirdly to present a case study in which the ratio-based modelling approach is applied to the determination of the DHL of security checkpoint facilities at two European airports. Using such an approach airport planners would be provided with an efficient and effective method to determine DHLs for a number of different passenger terminal facilities.

The remainder of this paper is organized as follows: In Chapter 2, the relevant literature on the description of DHL is reviewed. Subsequently, a ratio-based model and a model incorporating the effects of saturation are developed in Chapter 3. In Chapters 4 and 5, the results of both models are presented and discussed respectively. These findings are summarised and concluded in Chapter 6.

2. Literature

To define the relationship between DHL for airport terminal facilities and annual demand, it is necessary to understand the underlying demand functions, which describe how the facilities are frequented by passengers. Airport passenger terminals are complex systems consisting of a set of facilities (e.g., check-in, security checkpoints, emigration, immigration, baggage claim areas, etc.) which are frequented by a number of different passenger flows. Large hub airports usually accommodate different types of passenger flows, such as *local* and *transit*, as well as *domestic* and *international*. While local passengers either commence or terminate their journey at the airport, transit passengers only change airplanes. Domestic passengers are not subject to passport control or customs checks, while for international passengers usually the opposite is true.[1] Similarly, transit passengers are usually not required to use check-in facilities, and in case of passengers connecting between arriving and departing domestic flights, neither passport control nor immigration checks are required. For this reason, each passenger terminal facility is subject to an individual demand function, which, due to downstream propagation of passenger flows, strongly depends on demand functions of other facilities in terms of magnitude, mix and timing. Therefore, the demand function of a passenger terminal facility is an amalgam of different passenger flows scheduled to use the facility. Consequently, this makes the estimation of the DHL for an individual passenger terminal facility especially challenging. To this end, the literature mentions two distinct methods to estimate DHLs for passenger terminal facilities: (i) the *design day schedule method*, and (ii) the *ratio method*.

With the design day schedule method, airport planners create future flight schedules that specify departing and arriving aircraft, their payload, scheduled times, aircraft types, etc. for a number of *design days* in the future. In order to do this, current determinants of demand, such as fleet and airline mixes, load factors, transit rates, or arrival distributions are extrapolated (IATA 2017; Kennon et al., 2016, 2013; Robertson et al., 2002). Design day schedules are then used as inputs for discrete-event simulation models (Gatersleben and van der Weij, 1999; Saffarzadeh and Braaksma, 2000), agent-based simulations models (Hee and Zeph, 1998; Ma et al., 2011), accelerated time simulation models (Roanes-Lozano et al., 2004), or queuing theory models (Janic, 2007; McKelvey, 1988); these models are capable of reproducing the dynamics of the passenger flows and consequently determining the relevant DHLs for all airport passenger terminal facilities. It is for this reason that the design day schedule method is extensively used in airport strategic planning. Especially to model highly disaggregated passenger types or passenger flows (e.g., international vs. domestic passenger, local vs. transit passengers, etc.), the design day schedule method can be advantageous. However, airport planners have to be aware that the determination of design day schedules is a challenging and complex process which requires substantial input of resources, given the large number of factors to be considered.

The ratio method on the other hand, is based on the assumption that the ratio ρ between the design hour demand $dh_{i,T}$ (i.e., the DHL) for airport passenger terminal facility i and the aggregated annual demand D_T in year T can either be described with a constant ratio ρ_i,

$$dh_{i,T} = \rho_i \cdot D_T \tag{1}$$

Or, more generally, with a linear regression model (Horonjeff et al., 2010),

$$dh_{i,T} = f(D_T, \beta_i) + \varepsilon_T, \tag{2}$$

[1] In Europe, airports in the Schengen area usually differentiate between *Schengen* vs. *Non-Schengen* passengers, which can be viewed as an equivalent to Domestic vs. International passengers.

where β_i is a vector of unknown coefficients and ε_T is an error term. The unknown ratio ρ_i in model (1) and the unknown coefficients β_i of model (2) are estimated with an appropriate approximation method, such as the least squares method. In order to do so, a (large) dataset of historic observations for both the DHL $dh_{i,T}$ of facility i and the annual demand D_T for a number of years $T = 1, 2, \ldots, n_t$ is required. Once these unknown coefficients of a ratio-based model are estimated, it can be subsequently used by airport planners to translate future annual demand forecasts into DHL forecast figures with relative ease.

Due to its simplicity, the ratio-based method has been widely used in airport strategic planning, especially for passenger terminals. For instance, in FAA advisory circular 150/5360–7 (cancelled) produced a series of constant ratios between the TPHP and annual passenger volumes for US airports. Similarly, the UK Civil Aviation Authority defined a number of constant ratio values which specify the SBR measure as a function of ATM (Ashford et al., 1997). See Table 1 for a summary of commonly used figures.

Matthews (1995) suggested a linear model to forecast peak hour demand at airports operated by the British Airport Authority (BAA, now operating under Heathrow Airport Holding). Matthews correlated DHL with demand patterns on different time scales (hourly, monthly and day of the week). Wang and Pitfield (1999) estimated the coefficients of a linear regression model to describe the relationship between the overall DHL and annual throughput of all departing passengers for 48 Brazilian airports. Similarly, Urbazka and Wilken (1997) estimated the coefficients of a linear regression model which relates design hour movements to annual ATM. Subsequently, this model has been used to estimate the runway capacities of a number of German airports. Psaraki-Kalouptsidi (2010) applied the ratio method to a number of “holiday destination” airports on Greek islands which are associated with highly seasonal demand patterns. In order to better represent local conditions and characteristics, Psaraki-Kalouptsidi applied the k-means algorithm to generate clusters of airport types based on their hourly demand pattern. In addition to using annual ATM as an independent variable in their model, Wilken et al. (2011) incorporated variables categorizing airports according to their number and layout of runways and whether the airport in question is slot coordinated or not. The same method was used by Gelhausen et al. (2013), who identified which hub airports are currently capacity constrained or are most probably going to be so in the future.

The ratio method makes use of the fact that often the relationship between annual aggregated demand and the DHL demand of an airport facility can be described with a single ratio. As long as airport planners verify this assumption with real-world data, the method offers a number of strengths, which can be exploited accordingly. Most importantly, the ratio method requires less input data and parametrisation than the design day schedule method. The ratio method is reasonably robust with regard to its ability to handle exceptional and unpredictable events, such as the COVID-19 pandemic or the 9/11 terrorism attacks, since statistical outliers can easily be removed from the dataset of observations.[2] Moreover, new information, such as observations describing a new year, can be added without difficulty, thus enabling airport planners to keep their datasets and models up to date.

Table 1
Typical peak hour passengers as defined in FAA Advisory Circular 150/5360–7 (cancelled), from Ashford et al. (1997, p. 34).

Aggregated annual passengers D_T	ρ as percentage of annual demand
$\geq$ 30 million	0.035
20–29.999 million	0.040
10–19.999 million	0.045
1–9.999 million	0.050
500,000–999,999	0.080
100,000 to 499,999	0.130
<100,000	0.200

The ratio method, as it is presented in the literature, treats the airport and its underlying systems as *blackboxes* for which no prior knowledge is required for the modelling process. In fact, since it is a purely data-driven method, simply a large enough number of historic observations on annual demand and DHL are required to determine appropriate ratios or to estimate the coefficients of a regression model. However, in the context of emerging markets, where growth levels can be quite exceptional, historic observations are only of limited value to describe future demand. For any given airport, as annual demand volume grows, the absolute peak loads become less pronounced since demand is more equally distributed over time (De Neufville et al., 2013; IATA 2017). Moreover, for many airports the total number of ATMs per year is limited due to constraints imposed for operational, legal, environmental, or political reasons, which leads to *saturation effects*. For instance, the runway configuration of an airport, which determines the available number and orientation of runways, defines the absolute maximum annual ATM that can be accommodated (FAA 2015; ICAO 1987). Indeed, the declared capacity of an aerodrome, which is the capacity that considers all bottlenecks on the airside and the landside, is often substantially lower than the absolute maximum capacity of the runway system, especially if the runway system is not the most relevant constraining element. For instance, the capacity of Amsterdam Schiphol Airport is capped by Dutch law at 500,000 movements per annum (Schiphol Group, 2019). Similarly, at Zurich (ZRH) Airport political considerations limit runway capacity to approximately 70 hourly movements. Berster et al. (2015) suggest that airlines often schedule larger airframes to and from airports which are capacity saturated. Consequently, capacity saturation seems to have a rather direct impact on the average number of passengers per ATM, which in turn should be accordingly treated in a ratio-based modelling approach.

The ratio method appears only to have been applied to define DHLs more generally, such as the DHL for all departing passengers, rather than for specific airport passenger terminal facility sub-sets (e.g., check-in, the security checkpoints, or the immigration facility, etc.). This is most probably due to a lack of access to data sets which include detailed passenger flows in and out of terminal facilities. With conventional methods, such as surveys, the systematic collection of passenger flow data in terminal facilities over the course of many years may not be practical. In recent years however, some airport operators have started to collect data from automated passenger tracking systems (PTS) which measure passenger influx in and outflux from facilities as well as the movement of passengers within the terminal. These observations are carried out (i) in a conventional way by utilizing boarding pass readers, turnstiles, light barriers, etc., (ii) by tracking the Bluetooth or Wifi-signal of mobile and portable devices carried by passengers, such as the “SPOPS” system (Hansen et al., 2009), or “SITA iFlow” (Nikoue et al., 2015; SITA 2013), or (iii) by tracking the movement of passengers with the help of stereoscopic optical sensors and image recognition algorithms (Hänseler, 2020). As a consequence, large datasets describing passenger flows in airport passenger terminals can be and have been accumulated, which demonstrates the potential for these to be used for airport strategic planning applications (Raff and Wicki, 2019).

In the literature there is an emerging body of contributions dealing with the application of PTS data in airport planning. Schultz and Fricke (2011) employed data originating from a video-based PTS to determine a stochastic model of passenger movements in terminals describing tactical decision making and route choice by passengers. Hansen et al.

[2] The robustness of the method is only given, if the traffic patterns which ultimately define the DHL remain unchanged after a large-scale outlier event.

(2009) reported on the application of the SPOPS PTS at Copenhagen Airport, which is used to predict passenger flows and the resulting queue length and congestion levels in terminal facilities in real-time. The SPOPS system is used by the airport operator to manage resources and staffing as well as to provide passengers with detailed information on their expected waiting times at the facilities. Furthermore, Hansen et al. (2009) studied privacy concerns related to Bluetooth-based PTS in airport terminals tracking passenger movements within certain terminal areas for a limited period of time. Nikoue et al. (2015) used anonymized Wifi-based tracking data which describes the walking speed of passengers as well as the timing and magnitude of passenger flows obtained with SITA's "iFlow tool". This data was used to model the arrival process at the immigration facility of Sydney International Airport in Australia. Balakrishnan et al. (2016) proposed that by using passenger tracking and localization data, airports might be better capable of monitoring demand and managing staffing in the future. Marzouli et al. (2019) and Monmousseau et al. (2019) used a combination of mobile phone localization data (call detail records) and social media data (Twitter) to analyse the impact of weather-related disruptions on air transportation and airport operations in particular. Monmouseau et al. (2020) applied the same method to measure the drastic impact of the COVID-19 pandemic on airport operations. Burrieza et al. (2019) used call detail records in combination with airport surveys to characterize airport users (e.g., to distinguish between arriving, departing, or transit passengers or to identify visitors and staff, etc.). Finally, in the wake of the COVID-19 pandemic, Hänseler (2020) presented a method for the automatic monitoring of social distancing discipline based on measurement data gathered with the XOVIS passenger tracking system. PTS data has yet to be applied to airport strategic planning contexts more generally, and in particular to the determination of facility-specific DHLs.

3. Methods

3.1. Input data

In this study input data originating from ZRH Airport and an equally sized European airport, referred to as *Airport 2*, have been used. The dataset provided by ZRH Airport covers the years 2009–2019, while the data provided by Airport 2 covers the years 2012–2019. As such, the data provided can be divided into three distinct subsets: Annual data, ATM data, and passenger flow data. The annual data provides passenger and ATM information aggregated on a yearly basis. As such, the total number of enplanements (ATM and passengers) and the total number of departing passengers (the sum of local outbound and transit passengers) is provided. ATM data specifies the time of each movement and the number of local and transit passengers carried. Finally, passenger flow data, which is obtained by means of a PTS, describes the number of passengers entering a terminal facility $i = 1, 2, \ldots, n_i$,. In this paper, the security checkpoint facility at airport $j = 1, 2, \ldots, n_j$ is a function of time. For the application proposed in this study, all observations originate from a PTS dataset which covers the entire passenger population using the security checkpoint facility investigated.

The observed passenger influx data, which is measured with a PTS for facility i, airport j, and year T, is expressed with a time series $d^{P}_{i,j,T} = \{d^{P}_{i,j,T,t}\}_{t=1}^{n_t}$, where $t = 1, 2, \ldots, n_t$ and refers to 5-min interval segments within year T. Each segment contains data on the total influx of passengers in the facility (e.g., number of passengers entering the security checkpoint from 11:45 to 11:50 on April 02, 2020).[3] Subsequently, to smooth the 5-min interval data, a w-moving sum $\overline{d}^{P}_{i,j,T}$ is defined as a new time series on $d^{P}_{i,j,T}$ by applying the *movsum* function provided in Matlab. The *movsum* function calculates the moving average for a sliding window of size w, which, for the application presented here, is selected specifically to ensure that each window covers 60 min of data (i.e. ±30 min around the timestamp of the 5-min interval). In Fig. 1 an example of the observed data $d^{P}_{i,j,T}$ for the security checkpoint at ZRH Airport is shown as blue dots, while the moving sum $\overline{d}^{P}_{i,j,T}$ is displayed as a red line (Note, the data is plotted on two different y-axes).

3.2. Calculation of DHL for passenger terminal facility

Both in the industry and in academia there is no consensus on a universally applicable definition of the DHL. The literature suggests that the BHR, which is defined as "the value of passenger flow for which 5 % of the passengers encounter a flow rate at this level or above" (Matthews, 1995, p. 57), is a more typical peak hour, and should therefore be predominantly used for airport design (De Neufville et al., 2013). However, there are airports which apply the SBR, which in most cases tends to be higher than the BHR (Matthews, 1995). Subsequently, the selection of an appropriate DHL definition is usually carried out on a case-by-case and an airport-by-airport basis.

To meet this circumstance, the unsaturated and saturated DHL models presented in Chapters 3.3 and 3.4 can be applied to all DHL definitions without loss of generality. However, to provide the reader with a real-world example of the proposed planning methodology, the DHL definition as it is applied at ZRH Airport is used in this paper. At ZRH Airport the DHL for airport passenger terminal facilities is determined by means of the SBR referring to the 20th highest hour of passenger flow of the entire year. This contrasts with the literature, which recommends using the 30th highest hour for the SBR (Ashford et al., 1997; Matthews, 1995). According to ZRH Airport, the rationale behind opting for the SBR based on the 20th hour is grounded on considerations regarding the public's perception of service quality. Due to the operational concept of the local hub airline, most passenger terminal facilities at ZRH Airport experience only one daily peak period, whose duration is usually rather short. Consequently, by selecting a very restricting 20th highest hour for the DHL, the number of days on which customers might experience unacceptable service levels during this daily peak period can be limited significantly.

In light of this, for the purpose of this study the SBR for terminal facility i at airport j and for year T is calculated as follows. In a first step, the w-moving sum time series $\overline{d}^{P}_{i,j,T}$ of the observed passenger influx for facility i in year T is sorted in a descending order of the magnitudes of the observations. Then, this ordered list of hourly values is modified in an iterative procedure, which is referred to as the *rolling maximum*

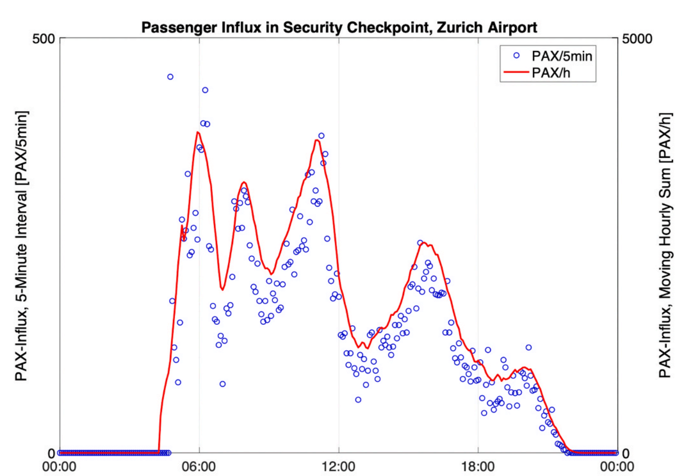

Fig. 1. Observed Passenger Influx in Security Checkpoint Facility for ZRH airport.

[3] Assuming a year with 365 days.$n_t = \frac{365d \cdot 24h \cdot 60min}{5min} = 105120$

algorithm. Starting with the first value of the ordered list, which refers to the highest observed hourly passenger influx of the entire year, all values within ±30 min from the timestamp of the first element of the list are removed from the list. Consequently, the algorithm iteratively applies the same procedure to the next element of the modified list until the end of the list is reached. An example is provided in Fig. 2, where the blue shaded elements of the ordered list are removed as they are within the specified time period of the first element of the list. In this way an ordered list of the maximum observed hourly passenger influxes into the facility of interest is generated. Finally, the SBR of facility i at airport j in year T, which is denoted as $dh_{i,j,T}$, is defined by selecting the 20th highest element of the list modified with the rolling maximum algorithm.

3.3. Unsaturated DHL model

Given the availability of (i) the observed DHL $dh_{i,j,T}$ for airport passenger terminal facility i of airport j in year T for unsaturated demand conditions, and (ii) the aggregated annual number of passengers $D_{j,T}$ (see Fig. 3), the transformation function of a linear regression model, called the unsaturated DHL model, is set out below:

$$dh^{US}_{i,j,T} = \beta^{US}_{i,j,0} + \beta^{US}_{i,j,1}\ln\left(D_{j,T}\right) + \varepsilon^{US}_{T} \tag{3}$$

where $\beta^{US}_{i,j,0}$ and $\beta^{US}_{i,j,1}$ are unknown coefficients of the linear regression model which are estimated with the ordinary least squares method in such a way that error term ε^{US}_{T} is minimized. In order to achieve better correlation between the model and the observed data, the natural logarithm of annual demand $D_{j,T}$ is used in the proposed transformation function.

The unsaturated linear DHL model is based on the rather simplistic assumption that the observed DHL is solely dependent on annual demand. In reality however, the theoretical maximum magnitude of the facility DHL is limited by a set of constraints, such as (i) the capacity provided by the runway system, (ii) the fleet mix operating from airport j, (iii) the average percentage of passengers using facility of interest i per ATM, and (iv) the ratio between passengers per ATM during the peak period for which the SBR is defined and the annual average of passengers per ATM. By means of the saturated DHL model the circumstances of such capacity constraints are taken into account.

3.4. Saturated DHL model

Many international airports are capacity constrained in terms of their runway system, which may only permit a maximum number of take-offs and landings per hour (De Neufville et al., 2013). Once this limit is reached, an airport can only grow to accommodate additional ATMs through substantially altering the performance of its runway system, for instance by building a new runway or by adopting new rules for runway usage, such as abolishing night curfews. Considering the airports included in this paper, the maximum hourly departure throughput of the runway system $\mu_{R,j}$ is known to be 44 and 41 movements per hour for ZRH Airport and Airport 2 respectively.

The number of passengers per ATM is limited and determined by a number of factors, among others the scheduled fleet mix of the airlines frequenting an airport. Fig. 4 shows the situation for 60 international airports,[4] depicting the relationship between the average number of passengers per ATM and the annual passengers as well as the number of runways available at the respective airport. This number is used as a readily available proxy for the maximum throughput of a runway system. It can be inferred from Fig. 4 that the average number of passengers per ATM (i) seems to rise asymptotically to a certain limit value and (ii) appears to be influenced by the available number of runways at an airport.

Consequently, this study uses a linear regression model to express the relationship between the annual average number of passengers per ATM $PAXATM_{j,T}$ for airport j versus the annual aggregated demand $D_{j,T}$ measured in passengers, the year of observation T, and the number of runways available at an airport of interest $n_{R,j,T}$. The transformation function of the proposed model is shown in Equation (4):

$$PAXATM_{j,T} = \beta^{PA}_0 + \beta^{PA}_1 \ln\left(D_{j,T}\right) + \beta^{PA}_2 T + \beta^{PA}_3 n_{R,j,T} + \varepsilon^{PA}_T \tag{4}$$

where β^{PA}_0, β^{PA}_1, β^{PA}_2 and β^{PA}_3 are unknown coefficients, and ε^{PA}_T is the error term which is assumed to be normally distributed.

The linear regression model proposed in Equation (4) specifies $PAXATM_{j,T}$, which is the annual average number of passengers per ATM. To determine the DHL of facility i, the number of passengers per ATM using facility i during the design hour which is denoted as $PAXATM^{dh}_{i,j,T}$ must be known. The relationship between $PAXATM^{dh}_{i,j,T}$ and $PAXATM_{j,T}$ can then be described by means of ratio $r_{i,j,T}$

$$r_{i,j,T} = \frac{PAXATM^{dh}_{i,j,T}}{PAXATM_{j,T}} \tag{5}$$

For the purpose of this study historic observations of $PAXATM^{dh}_{i,j,T}$ for ZRH airport and Airport 2 are determined with PTS data originating from boarding pass readers installed at the entrance of the security checkpoints as well as ATM data provided by the airports. Fig. 5 depicts observational data for $r_{i,j,T}$ measured at ZRH Airport and Airport 2 by means of boxplots in which the median of the observed ratio is illustrated with a red horizontal line.

As can be inferred from Fig. 5, the ratios $r_{i,j,T}$ for ZRH Airport and Airport 2 seem to be subject to fluctuations and outliers. For reasons of simplicity in this study it is assumed that $r_{i,j,T}$ can be modelled with a constant which is estimated with the median of the observed data for $r_{i,j,T}$. The median has been chosen since it is known to be less susceptible to outliers than, for instance, the arithmetic mean.

Finally, the saturated DHL model for facility i is expressed as

$$dh^{S}_{i,j,T} = \mu_{R,j} \cdot PAXATM_{j,T}\left(D_{j,T}, T, n_{R,j,T}, \widehat{\beta}^{PA}_0, \widehat{\beta}^{PA}_1, \widehat{\beta}^{PA}_2, \widehat{\beta}^{PA}_3\right) \cdot \widehat{r}_{i,j,T} \tag{6}$$

where μ_j is the maximum departure throughput capacity. This depends on the maximum number of take-offs per hour which can be handled by the runway system of airport j. $\widehat{\beta}^{PA}_0$, $\widehat{\beta}^{PA}_1$ $\widehat{\beta}^{PA}_2$, and $\widehat{\beta}^{PA}_3$ refer to the coefficient estimates of the linear regression model introduced in Equation (4), and $\widehat{r}_{i,j,T}$ is the estimated value of ratio $r_{i,j,T}$. As such, for ZRH Airport, a ratio of $\widehat{r}_{i,j,T} = 0.88$, and for Airport 2, a ratio $\widehat{r}_{i,j,T} = 0.97$ is estimated.

3.5. Determining critical demand and DHL

By comparing the unsaturated and the saturated DHL model for a facility i, its critical annual demand and critical DHL can be determined. The critical annual demand is facility-specific and indicates the threshold at which capacity constraints limit the unsaturated growth of the DHL. Below the critical demand threshold, the unsaturated model can be applied to forecast DHLs, since the facility in not affected by capacity constraints. In contrast, above the threshold, the saturated model should be applied by airport planners in order to determine realistic DHL estimates.

[4] Fig. 4 is based on annual traffic data for both passengers and ATM of the following international airports: ABQ, AGP, AMS, ARN, ATH, ATL, AUH, BCN, BHX, BKK, BOS, BRU, BUD, BUR, CAN, CGN, CPH, DAL, DEN, DUB, DXB, EDI, FRA, GLA, HAM, HKG, ICN, LAX, LGA, LGW, LHR, LIN, LIS, LTN, MAD, MAN, MCI, MEL, MUC, MXP, ORD, ORY, OSL, PBI, PDX, PEK, PER, PMI, PRG, PVD, PVG, SAT, SFO, SIN, STN, SVO, SYD, VIE, WAW, YYZ, and ZRH. The raw data has been sourced from (i) the *Airport Statistics and Data Centre* of Airport Council International (ACI) (https://aci.aero/data-centre/) and (ii) Wikipedia.

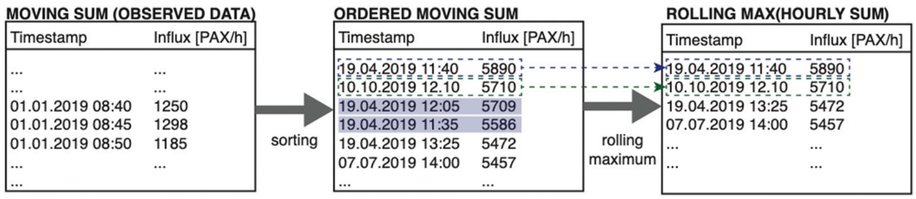

Fig. 2. Proposed calculation procedure for DHL.

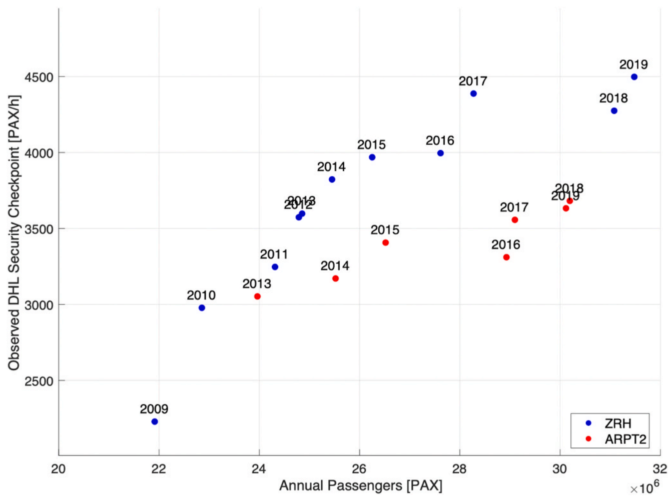

Fig. 3. Observed DHLs at security checkpoint (20th peak hour) for ZRH Airport and Airport 2.

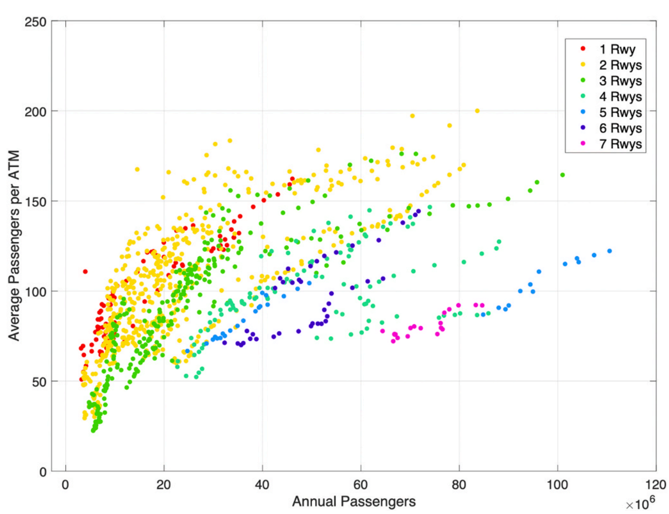

Fig. 4. Average Passengers per ATM in function of annual passengers and number of runways.

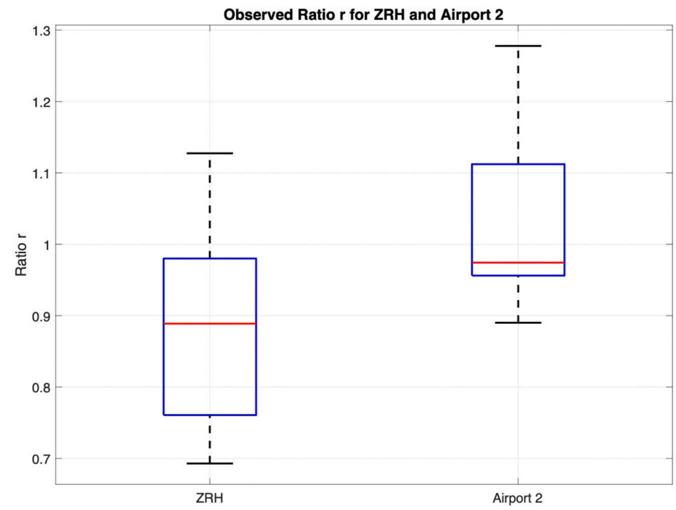

Fig. 5. Ratio r between $PAXATM^{dh}_{i,j,T}$ and $PAXATM_{j,T}$ for ZRH airport and airport 2.

4. Results

4.1. Unsaturated DHL model

In Fig. 6 the observed DHLs for both ZRH and Airport 2 are plotted with blue and cyan dots, while the best fit of the unsaturated DHL model, based on the transformation function mentioned in Equation (3), is displayed as a red line and the corresponding 95 % confidence interval is illustrated with black dashed lines. Furthermore, the actual DHL vs. predicted DHL plot illustrates residuals of the regression model. Table 2 represents the estimated coefficients $\widehat{\beta}_0^{DH}$ and $\widehat{\beta}_1^{DH}$ as well as parameters describing the quality of fit for a number of different model options. “Transformation” refers to the applied transformation function, “airport j” specifies the applied input data ($j = 1$ refers to ZRH, $j = 2$ to Airport 2), “RSME” contains the root-mean-square error and “R^2” includes the coefficient of determination.

4.2. Saturated DHL model

Table 3 summarises the estimated coefficients $\widehat{\beta}_0^{PA}$, $\widehat{\beta}_1^{PA}$, $\widehat{\beta}_2^{PA}$, and $\widehat{\beta}_3^{PA}$ and the quality of fit parameters of the average passenger per ATM model, which is a substantial part of the saturated DHL model. As such, the average passenger per ATM model is applied to the dataset presented in Fig. 4. Since the airports providing passenger flow data for this study have either 2 or 3 runways, only a subset of data, consisting of those airports whose total available number of runways is either 2 or 3, is used for the determination of the coefficients.

Fig. 7 depicts results of the average passenger per ATM model, based on input data of airports with 2 or 3 runways (blue dots). The data of ZRH Airport and Airport 2 is highlighted in magenta and cyan respectively. The best model fit, in this case for an airport with 2 runways, is displayed as a red line, while the 95 % confidence interval is shown with black dashed lines. As in Fig. 6 the residuals are illustrated in a separate plot.

4.3. Comparison of saturated and unsaturated model

In Fig. 8 the critical demand for the security checkpoint at ZRH Airport is identified at roughly 45.3 million annual passengers and a DHL of 6632 PAX/h. The red and black solid lines refer to model predictions of the unsaturated and saturated model based on historical data, while the dashed lines indicate predictions of future input data.

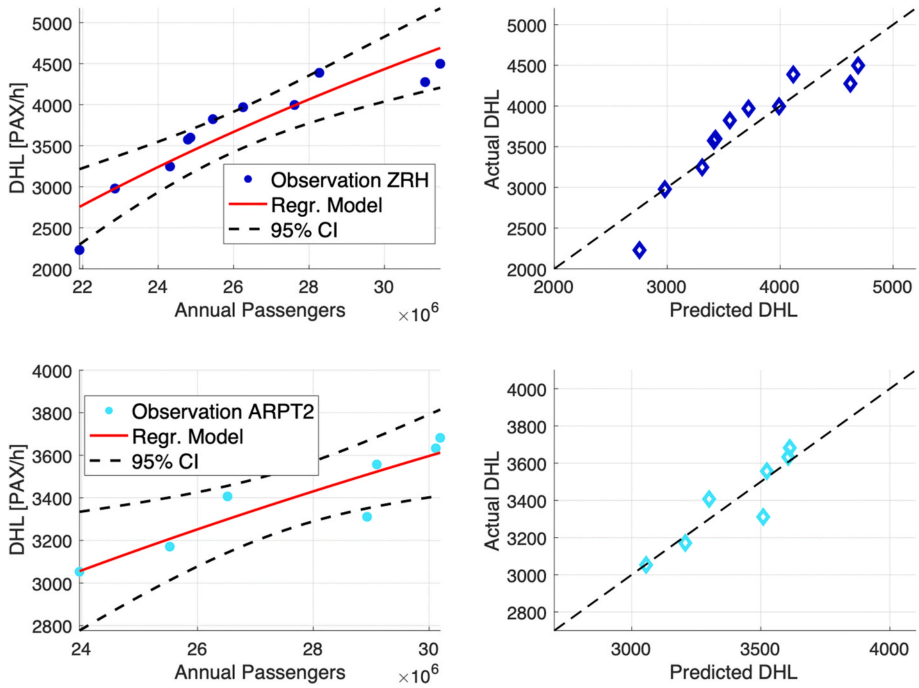

Fig. 6. Unsaturated DHL model fitted to observed data of the two airports used in this study.

Table 2
Estimated coefficients and quality of fit for unsaturated DHL model.

Transformation function	Equation (3)	Equation (3)
Airport	ZRH	Airport 2
Estimated Coefficients	$\widehat{\beta}_{i,j,0}^{US} = -8.76E4$	$\widehat{\beta}_{i,j,0}^{US} = -3.79E4$
	$\widehat{\beta}_{i,j,1}^{US} = 5.34E3$	$\widehat{\beta}_{i,j,1}^{US} = 2.41E3$
p-values of estimated coefficients	$p(\widehat{\beta}_{i,j,0}^{US}) < 8.55E\text{-}5$	$p(\widehat{\beta}_{i,j,0}^{US}) < 6.53E\text{-}3$
	$p(\widehat{\beta}_{i,j,1}^{US}) < 6.22E\text{-}5$	$p(\widehat{\beta}_{i,j,1}^{US}) < 4.55E\text{-}3$
F-statistics vs. constant model	49.2, p-Value < 6.22E-5	23.8, p-value < 4.55E-3
RSME	279	109
R2	0.845	0.826
Number of observations	11	7
Degrees of freedom	9	5

Table 3
Estimated coefficients and quality of fit of average passenger per ATM model.

Transformation function	Equation (4)
Estimated coefficients	$\widehat{\beta}_0^{PA} = -2.52E3$
	$\widehat{\beta}_1^{PA} = 4.18E2$
	$\widehat{\beta}_2^{PA} = 9.72E\text{-}1$
	$\widehat{\beta}_3^{PA} = -1.57E2$
p-values of estimated coefficients	$p(\widehat{\beta}_0^{PA}) < 2.13E\text{-}26$
	$p(\widehat{\beta}_1^{PA}) < 2.35E\text{-}209$
	$p(\widehat{\beta}_2^{PA}) < 1.19E\text{-}16$
	$p(\widehat{\beta}_3^{PA}) < 1.46E\text{-}25$
F-statistics vs. constant model	765, p-Value < 4.42E-229
RSME	18.6
R2	0.751
Number of observations	764
Degrees of freedom	760

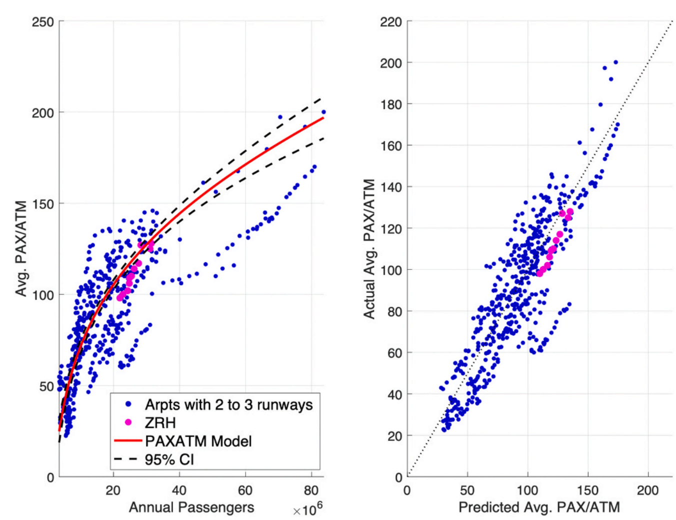

Fig. 7. Model fit for average passenger per ATM vs. annual PAX and number of available runways at an airport.

5. Discussion

5.1. Discussion of model results

The unsaturated DHL model is based on a transformation function as in Equation (3) which considers the natural logarithm of the annual demand. During intensive testing this type of transformation function was found to be the most optimal in terms of performance. This is most probably due to the fact that with increasing traffic, the growth of the DHL is often less pronounced (De Neufville et al., 2013; Kennon et al., 2013). Large airports might apply certain pricing schemes such as peak-pricing or congestion pricing to control demand, or regional flights may be substituted with rail connections (Berster et al., 2015). Moreover, especially at airports with either high traffic volumes or capacity constraints, the hourly, daily, monthly and seasonal variation in the number of flights, and thereby also the variation in the number of

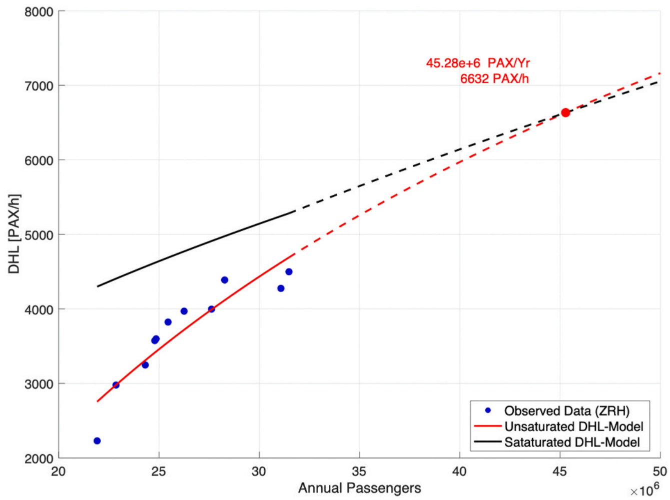

Fig. 8. Identification of critical annual demand for the example of the security checkpoint infrastructure at ZRH.

passengers per unit time becomes less pronounced with increasing annual demand. This has a direct impact on the growth of the DHL (Reichmuth et al., 2011; Wilken et al., 2011). Unfortunately, however, the effects reported in the literature cannot be fully confirmed in this study, since no input data originating from international airports with an annual demand of more than 50 million passengers is available. Considering the quality of fit of the unsaturated DHL model (see Table 2), the model for ZRH is significant at the 5 % level.

The saturated DHL model is based on three components: the hourly departure throughput capacity of an airport, the linear regression model describing the average number of passengers per ATM and the model for ratio $r_{i,j,T}$. Considering the departure throughput capacity of an airport, it is important to acknowledge that even though the method proposed in this paper assumes the presence of a single value for $\mu_{R,j}$, the actual throughput of a runway system is a dynamic property which depends on the runway configuration currently in use, weather conditions, the fleet mix, the share of departures and arrivals, etc. (De Neufville et al., 2013). For this reason, it is advisable to use various different values of $\mu_{R,j}$ in order to explore the influence of runway capacity on the output of the saturated DHL model. The model for the average number of passengers per ATM is based on data sourced from Airport Council International and Wikipedia. Based on results presented in Figs. 4 and 7, it can be inferred that the relationship between the average number of passengers per movement and annual passengers may approach a certain limit value. This observation is supported by the literature. According to Berster et al. (2015), airlines tend to schedule aircraft with higher seat capacity to airports with high (er) demand and airports which are capacity constrained. Since the variety of aircraft types, especially in the widebody aircraft market segment is limited, there will be a natural limit of maximum possible number of passengers per ATM. Indeed, Berster et al. (2015) report that in the case of Emirates Airlines, which operates almost exclusively large widebody aircraft, the average number of passengers per ATM is approximately 240.

Additionally, one of the independent variables considered for the average passenger per ATM model is the number of runways available at an airport. This variable has been chosen as a proxy for the maximum throughput of a runway system, since it is readily available in the public domain. Nevertheless, airport planners must handle this variable with care for real-world applications. In reality, airports with multiple runways often only operate some of the available runways simultaneously. Consequently, the proposed model might not fully reflect daily operations. To partially cope with this deficiency, the results presented in Table 3 and Fig. 7 are solely based on input data covering airports with 2 or 3 operational runways, since at ZRH Airport and Airport 2 no more than 3 runways are available for use.

Finally, the existence of estimated ratios $\widehat{r}_{i,j,T}$ whose value is close to 1 (see Chapter 3.4) or even larger than 1 is especially interesting, since one could assume that this should not be possible. In reality the opposite is true, as ratio $r_{i,j,T}$ combines two separate effects in one single constant, namely (i) the number of passengers using facility i per ATM and (ii) the ratio of design hour passengers per ATM to annual average passengers per ATM. While the first effect can never exceed an aircraft's capacity, it is perfectly legitimate to assume a higher utilization of aircraft during peak periods than the yearly average. Finally, for reasons of simplicity, it has been decided to estimate ratio $r_{i,j,T}$ with the median of the observed data rather than applying a more sophisticated regression model. Given the fact that the DHL models presented in this paper are applied in the area of airport strategic planning, which is subject to significant uncertainty, such a simplification is justifiable, as long as the planners are aware of the accompanying limitations.

5.2. Implications of presented models for airport strategic planning

Both the unsaturated as well as the saturated DHL model are designed for an application in the domain of airport strategic planning. In strategic planning demand forecasts are usually provided on the aggregated level, such as annual passengers or annual ATM. Consequently, the presented models can be used by airport planners to determine future DHL loads of airport passenger terminal facilities, which then in turn can be translated into future facility requirements.

Additionally, the determination of *critical demand* levels (see Chapters 3.5 and 4.3) for airport passenger terminal facilities may provide airport planners with novel and valuable insights that could be applied in the development of strategic plans. As such, airport planners will often have to find the optimal choice between a series of capacity expansion projects, given financial and budgeting constraints. This task can be achieved with capacity planning models, which in their most basic form evaluate the "fundamental trade-off between the economies-of-scale savings of large scale expansion versus the opportunity cost of installing capacity before it is needed" (Van Mieghem, 2003, p. 273). The literature presents a number of different capacity planning model approaches for the strategic planning of airport passenger terminal infrastructure. These allow the determination of optimal capacity levels by various means: a multistage stochastic programming model (Solak et al., 2009), a two-stage stochastic programming model (Sun & Schonfeld, 2015, 2017), an analytical model (Chen and Schonfeld, 2013), and a cost-benefit analysis (Yoon and Jeong, 2015). Given the large solution space of capacity planning optimization problems, the determination of appropriate solutions can be computationally intense. With the saturated DHL model presented in this paper, the solution space of existing capacity planning models could be substantially reduced, as it suggests an upper limit for the optimal capacity level. In fact, the saturated DHL model defines for each facility i a *planning envelope* $dh^S_{i,j,T} = f(D_{j,T}, \mu_{R,j},\ T,\ n_{R,j,T}, \widehat{\beta}^{PA}_0, \widehat{\beta}^{PA}_1, \widehat{\beta}^{PA}_2, \widehat{\beta}^{PA}_3, \widehat{r}_{i,j,T})$, which specifies for each annual demand level $D_{j,T}$ whether the provision of $K_{i,j,T}$ units of infrastructure is advisable or not. For reasons of simplification, it is assumed that the maximum hourly throughput of facility i can be expressed as $\tau_{i,j,T} = \mu_{i,j,T} K_{i,j,T}$, where $K_{i,j,T}$ refers to the operational number of infrastructure units (e.g., check-in desks, or security check lines), and $\mu_{i,j,T}$ describes the hourly service rate of a single infrastructure unit of facility i. Using this model airport planners are advised to provide only as many units of capacity so that the maximum hourly throughput of the facility $\tau_{i,j,T}$ is within the planning envelope $dh^S_{i,j,T}$.

$$\tau_{i,j,T} \leq dh^S_{i,j,T} \tag{7}$$

Once the critical number of units of capacity $K^C_{i,j,T} = \frac{dh^S_{i,j,T}}{\mu_{i,j,T}}$ is reached, the provision of additional units of capacity is not advisable from an operational point of view, since (i) the observed DHL of facility i will never exceed $dh^S_{i,j,T}$ under the constraints considered in the saturated DHL model, and (ii) the overprovision of capacity substantially contributes to the above-mentioned opportunity costs of installing capacity before it is actually required. Nevertheless, airport planners may sometimes still have good reason to deliberately overdesign an airport passenger terminal facility, namely when economies of scale can be realized.

6. Conclusion

This paper presents two different models which allow the estimation of DHLs for airport passenger terminal facilities where the aggregated demand data in the form of the number of annual passengers is given. In this study the SBR has been used to determine the DHL of an airport facility, since this is the method used at ZRH Airport. Without any loss in generality however, the methodology presented in this paper can also be applied to other DHL definitions, such as the BHR, which are used at other airports. The unsaturated DHL model is solely based on the observed relationship between annual demand and the DHL, while the saturated DHL model considers a number of capacity constraining factors, such as the throughput capacity of the runway system, or information regarding the number of passengers transported per ATM. The results presented in this study indicate that overall, both the unsaturated and the saturated DHL model led to outcomes which are significant at the 5 % level. In this light, the suggested methodology could be used in airport strategic planning, where it may provide planners with an intuitive and efficient way of translating aggregated annual demand figures into DHL estimates for passenger terminal facilities. Additionally, the saturated DHL model could be used to determine whether the installation of a certain capacity level is preferable from an operational perspective. It is important to mention that while the proposed methodology is generically applicable to airports, the model parametrisations presented are only applicable to the security checkpoint facilities at ZRH Airport and Airport 2. Nonetheless, these parameters may provide a good starting point for other applications at different airports or facility types.

Several extensions to this research are possible. By including data sources of additional airports and broadening the scope to consider facilities other than security checkpoints, both the transferability and generality of the proposed models can be tested. This has the potential to improve and refine various methods in the area of planning, design, and sizing of airport passenger terminal facilities, as well as infrastructure areas that depend on these, such as belly-hold freight operation chains (Merkert and Ploix, 2014). Furthermore, the usage of passenger movement data obtained through optical tracking systems would be particularly interesting, since this could offer additional insights for airport planners (e.g., dwell times, queue lengths, movement patterns, etc.). The saturated DHL model can be further refined by considering additional factors that constrain the DHL of a facility, such as the effects of limitations in ground access infrastructure or the influence of different arrival patterns of passengers (Postorino et al., 2019). Finally, it was possible to improve and simplify the solution procedure of existing capacity planning models applied to airport strategic planning with the proposed saturated DHL model as discussed in Chapter 5.2.

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CRediT authorship contribution statement

Manuel Waltert: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Jan Wicki:** Conceptualization, Methodology, Validation, Writing – review & editing. **Edgar Jimenez Perez:** Supervision, Writing – review & editing. **Romano Pagliari:** Supervision, Writing – review & editing.

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