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# A parametric method to enhance decision-making in airport terminal development

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ABSTRACT

Business cases and investment decisions for airports and passenger terminals are generally based on annual flight and passenger number forecasts. However, the design of a new passenger terminal is based on much shorter-term demands, typically a "peak hour". Conventionally there are two methods for bridging the gap between annual demands and these short-term demands: a design day schedule, or a ratio-based method. There are important practical and theoretical limitations with these methods. In this paper, a complementary method is proposed that provides an improved theoretical basis for determining short-term demands and which can form part of a more informed decision-making process. Its application to a recent terminal design case is discussed.

## 1. Introduction

Annual air transport passenger numbers have risen from 0.31bn in 1970 to a peak of 4.56 bn in 2019 (World Bank, 2022). Despite the profound impact on aviation of the global pandemic (passenger numbers dropped to 1.81 bn in 2020) the International Air Transport Association (2022) expects passenger numbers to recover to 4.0 bn by 2024 and investment in airport projects continues. Airports Council International (2021) suggests that US$2.4 trillion in capital investment would be needed by 2040 to maintain and expand current infrastructure. One industry report notes over one thousand airport projects (where each project exceeds US$25 million in value) in the pipeline at the start of 2022, with a combined value of US$1.6 trillion (Airport Technology, 2022).

Business cases and investment decisions for airports and passenger terminals are generally based on annual flight and passenger number forecasts since income is, to a large extent, determined by the number of passengers served. Approaches to forecasting annual demand have been described over many years. Zuñiga et al. (1979) use factors such as demographics, economics, transport, and tourism to generate forecast demands in the case of Mexico City. This produced estimates for demand 15 years in the future, though the range in estimates is rather wide: from c. 17 million to c. 28 million passengers per year. Although focussed on predicting demand for aircraft (rather than passengers), Lenormand (1989) also uses GDP (gross domestic product) and other economic factors such as fuel prices, inflation, and interest rates as well as number of aircraft market factors such as fleet characteristics in a system dynamics model. Rather than absolute predictions, the model is used to explore "what if" scenarios. Karlaftis et al. (1996) propose a method to develop time-series models with explanatory variables such as gross national product, population, income, and the price of travel. Using a number of case studies, the authors note the difficulty of creating a universal demand model: each case study requires a different model and explanatory variables. Xie and Zhong (2016) use a neural network approach to forecast passenger numbers at Changi Airport in Singapore which also uses GDP and population forecasts as inputs. They note, that while the model and historical results are mostly close, the impact of financial crises and the SARS pandemic led to the largest errors in the results for 1997, 2009, and 2014. Zhang (2020) considers nineteen potential economic and social indicators from which a subset is selected to forecast passenger numbers for Mianyang City in China. However the actual accuracy of these forecasts will only become apparent in the coming years. Zuñiga et al. (1979) note that half the five-year Federal Aviation Administration (FAA) forecasts were in error by more than 20%. Maldonado (1990) compares 23 masterplan forecasts with actual outcomes, finding that: (a) the forecasts are always "wrong"; (b) the

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farther away the time forecast horizon, the worse the estimate; and (c) there is no relation between forecast accuracy and airport size. The spread in results was large. The 15-year forecasts yield forecast to actual ratios ranging between 0.66 and 3.1.

In contrast to the typical business case perspective, the required capacity in an airport terminal (and hence the cost of facilities) tends to be determined by short-term, peak demands with typical timescales of an hour or less. The FAA provides guidance on airport terminal planning (Federal Aviation Administration, 2018) in which annual passenger demands are first used to determine the broad scale of facility requirements. Then a process of estimating short-term, peak demands is carried out. The dichotomy in timescales between revenue drivers (annual passenger numbers) and cost drivers (the size of facilities and infrastructure to deal with short-term demands) is a risk at the heart of the business cases for airport capital programmes (Ashford et al., 2013; Betancor et al., 2010).

Designing facilities for an absolute peak in demand is generally uneconomic, and a lower design basis is generally chosen (Ashford et al., 2013). It is necessary to choose a demand level which, while below the absolute peak, is sufficient to accommodate the absolute peak "without serious overload". Three of peak demand metrics are often used.

1. Standard Busy Rate or SBR (which is the same as the 30th Busy Hour taken from road engineering).
2. Typical Peak Hour Passengers or TPHP (which is generally used in the US and is the peak hour of the average day of the peak month).
3. Busy Hour Rate or BHR (which was adopted by the British Airports Authority and, in that case, was the demand above which 5% of total annual traffic operates beyond the design basis (Matthews, 1995; Reichmuth et al., 2011)).

In this study we used these definitions of SBR and BHR. The same metrics, albeit with different parameters (e.g. SBR using the 40th or 20th busy hour (Aertec, 2018; Waltert et al., 2021), or BHR covering all but 2% of annual traffic), can be used. Wang and Pitfield (1999) use historical data to compare and contrast peak and other busy hour measures. Jones and Pitfield (2007), compare and contrast results of facility requirements based on a range of different "busy hour" rates definitions of the sort described above and conclude that "standard formulae are an inadequate method of devising area requirements alone, however they do provide a starting point".

Irrespective of the definition of the busy hour rate, the numerical value of a given rate is determined by an analysis of historical data – a previous year's data from which the chosen metric is calculated. In the case of a brand-new airport, there is no historical track record. Therefore, if such a metric is to be used as a forecast design parameter, it must be estimated in a different way.

Conventionally these different timescales are bridged in one of two ways: (a) ratio methods or (b) design day schedule methods. The first method uses empirically observed ratios of short-term demands to annual demands to inform the basis of design for a new terminal. The ratio method has a long history. Braaksma and Shortreed (1976) refer to an early FAA publication on the design of airport terminal buildings (Federal Aviation Administration, 1960) in which they state that an empirical relationship between the forecasted peak-hour passenger flows and facility space requirements was given. However, this inherently combines (a) an annual to peak factor with assumptions about (b) the dwell time of passengers in a given facility and (c) the amount of space to be provided per passenger. Subsequent work has treated these factors separately. Fundamentally, the relationship between number of passengers in a given facility, the flow rate into the facility, and dwell time of passengers in the facility is given by Little's Law from queuing theory (Little, 1961). A range of queuing models have been proposed that naturally include process/dwell times. McKelvey (1988), for example, sets out a conceptually simple analytical queuing model for departing passenger processes, while Stolletz (2011) models queues arising from time-varying demands and assesses their effectiveness in the context of the passenger check-in process. The amount of space per passenger is often addressed through a consideration of the "level of service" (LOS) (Ashford, 1988). The LOS approach has been adopted and continued to be developed over time (Ballis et al., 2002; Brunetta et al., 1999; Correia et al., 2008a, 2008b; Correia and Wirasinghe, 2004, 2007; de Barros et al., 2007; Di Mascio et al., 2020; Kim and Wu, 2021). Dwell times and levels of service are used to inform space requirements, but they depend on input flow demands, which, using a ratio method, can be linked to annual demands. The ratio method continues to be actively developed and elaborated (Waltert et al., 2021).

The second method uses a design day schedule (Kennon et al., 2016). The schedule is created to represent a busy day during the design basis year. The schedule is then analysed to derive the short-term demands (Kennon et al., 2013). Bhadra et al. (2005) report some success (94% of forecasts were within 25% of actual results) in forecasting flight schedules for larger airports in the United States, but these were based on incremental changes to a pre-existing baseline schedule (rather than a forecast schedule for a completely new airport). Kolind (2020) notes that design day schedules give a "false sense of certainty and accuracy" because users argue that the analysis has been done "on a very detailed, flight-by-flight level", an impression reinforced by the fact that creating a design day schedule itself requires a lot of work and includes many assumptions.

As Odoni and de Neufville (1992) highlight a generation ago, there are still three problems associated with the typical terminal design process: (a) questionable accuracy of forecast schedules; (b) the use of simple ratios to convert a passenger flow rate, and desired level of service, into area requirements; and (c) results which are effectively single-point estimates. Despite these acknowledged drawbacks these same methods are still used in the industry (International Air Transport Association, 2004, 2019).

This type of strategic decision-making problem has been labelled as "decision-making under deep uncertainty" (Kwakkel et al., 2012). There is an emerging body of literature in this field. The use of modelling software and a scenario generator has been proposed (Lempert et al., 2003). A system design methodology which emphasises the iterative interaction between modelling and engagement with stakeholders has been suggested (Yamada et al., 2017). We take these two insights to inform the development of the method proposed here: (a) the ability to generate a range of plausible demand scenarios and (b) to express parameters defining demand peakiness in terms which are easily understood by a range of stakeholders.

We identify the following characteristics of relevance to the two traditional methods and to the parametric method proposed in this paper.

**Fixed MPPA:** Ability to reflect a single, target value for the number of passengers per year in the design year (where MPPA stands for millions of passengers per annum).

**Variable MPPA:** Ability to reflect alternative annual demand scenarios by simple parametric adjustment of assumptions.

**Fixed Peakiness:** Ability to reflect a single demand profile with its inherent peakiness.

**Variable Peakiness:** Ability to reflect alternative demand profiles with different degrees of peakiness by simple parametric adjustment of assumptions.

**Fine Detail:** Ability to provide fine-grained detail (e.g. flight-by-flight information) typically used in detailed analysis and simulation.

**Rapid Development:** Ability to produce results rapidly, from the given method.

**Probabilistic Output:** Ability to produce results reflecting a range of input assumptions and their probabilities.

**Type of Peak Measure:** Description of the type of peak measure provided by the given method.

How these characteristics apply to the schedule-based, and ratio-based, methods, are summarised in Table 1. The characteristics of the

**Table 1**
Comparison of methods.

| Factor | Schedule | Ratio | Parametric |
|---|---|---|---|
| Fixed MPPA | ✔ | ✔ | ✔ |
| Variable MPPA | ✖ | ✔ | ✔ |
| Fixed Peakiness | ✔ | ✔ | ✔ |
| Variable Peakiness | ✖ | ✖ | ✔ |
| Fine Detail | ✔ | ✖ | ✖ |
| Rapid Development | ✖ | ✔ | ✔ |
| Probabilistic Output | ✖ | ✖ | ✔ |
| Type of Peak Measure | Absolute | BHR/SBR | BHR/SBR |

parametric method (which is proposed in this paper) are also shown in the table.

In this paper, we aim to provide a method whereby a range of stakeholders (terminals designers, investors, etc.) can constructively challenge design day schedules, which do not naturally embody the concept of SBR or BHR, so that a common understanding of the plausibility of the design basis can be achieved, with reference to other airport terminals' observed demand patterns.

The distinguishing features of the proposed method are that it: (a) supports rapid assessments of demands with different degrees of "peakiness" and (b) provides probabilistic outputs. It shares the convenience and speed of calculation of the traditional ratio method, along with measures of "peak" demand based on either SBR- or BHR-type metric. The design day schedule method provides complementary features, most obviously the fact that a detailed flight schedule is produced which allows detailed modelling/simulation of demands including passenger processing, baggage processing, and aircraft movements and stand usage. However, the construction of such a schedule can be time-consuming. Furthermore, a given schedule reflects but one view of the demand and, as the planning horizon goes more than a few years into the future, the difference between actual and forecast demands is seen to grow materially. Just as the overall demand (e.g. daily or annual passenger numbers) is "baked in" to a forecast schedule, so too is the inherent "peakiness" which arises from the specific choice of aircraft arriving and departing patterns. This makes it hard to use a design day schedule method in a scenario planning context to explore different demand scenarios. A design day schedule (in isolation) does not provide an indication of an SBR or BHR "peak" demand because it provides a single demand value: the demands during other hours, throughout a forecast year, are not necessarily calculated.

The parametric method can be applied in two cases (see Fig. 1). In Use Case A, it is used to make an estimate of the SBR (based on the parameters effectively embedded in the design day schedule), in contrast to the schedule method which gives an estimate of the absolute peak. In Use Case B, some or all of the parameters used as inputs to the parametric method are taken from other sources (e.g. historical data from "similar" terminals, or simply alternative scenario assumptions). This allows a range of demand scenarios to be generated which can provide context to the single point estimate that arises from the schedule method applied in isolation.

In Section 2 we describe the development of the proposed method. In Section 3 we present a case study in which the conventional and parametric methods are compared in the context of a design workflow. A discussion of the results is given in Section 4, together with suggestions for further refinements of the proposed method. Brief conclusions are given in Section 5.

## 2. Parametric method development

This section describes the development of the proposed method. The flight schedule data upon which the analysis is based is first described. Then different metrics of short-term demand are explained and compared. One is chosen for the subsequent analysis. The observed relationship between annual demands and short-term demands is explored and the two models compared. The concept of operating periods is introduced as a way of parametrising the patterns of demand over three different timescales. Finally, a Poisson-based model is shown to offer an improved fit to the observed data.

### 2.1. Data

The dataset underpinning this study is historical OAG information on scheduled passenger flights in 2018 (OAG Aviation, 2022). The contents of the dataset used in this study are shown in Table 2, which shows field names, an example of an entry, and supporting notes.

The dataset covers 4050 airports and 38.0 million departing flights

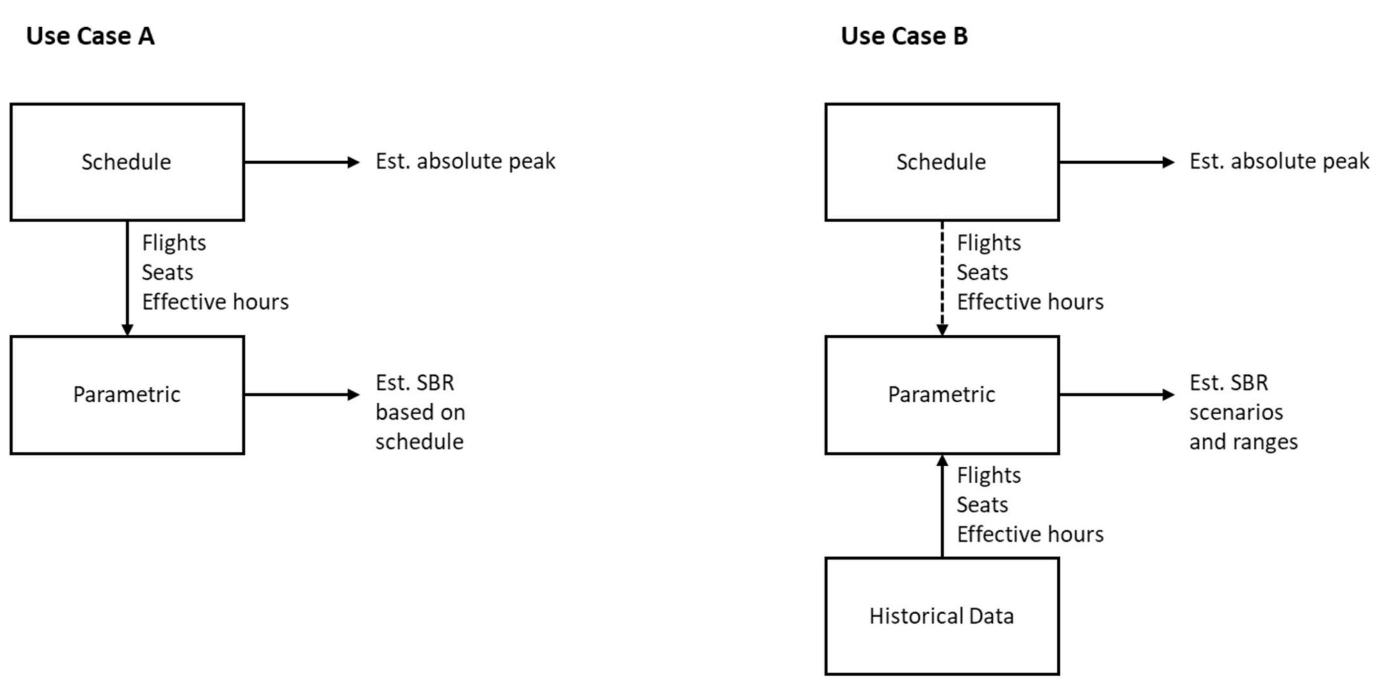


**Fig. 1.** Application of the parametric method.

**Table 2**
Dataset contents.

| Field | Example | Notes |
|---|---|---|
| Carrier Code | W6 | Airline: Wizz Air |
| Flight No | 3782 | |
| Dep Airport Code | FMM | Memmingen Airport |
| Dep Terminal | 0 | Terminal number/identifier |
| Arr Airport Code | SBZ | Sibiu International Airport |
| Arr Terminal | 0 | Terminal number/identifier |
| International/Domestic | International | Flag |
| Local Dep Time | 1405 | hhmm |
| Local Arr Time | 1700 | hhmm |
| Local Arr Day | 0 | −1,0,+1 according to time zones |
| Elapsed Time | 01:55 | hh:mm |
| General Aircraft Code | 32S | |
| Specific Aircraft Code | 320 | Airbus A320 |
| GCD (km) | 1078 | Great circle distance |
| Seats (Total) | 180 | |
| Time series | 29/03/2018 | Date of departure flight |

with 5.6 billion seats. The International Civil Aviation Organization (2019) reports that, in 2018, there were 37.8 million departing flights, suggesting that the dataset used is relatively comprehensive. According to World Bank (2022) 4.24 bn passengers flew in 2018, suggesting a global average passenger seat factor of 76% (i.e., the ratio of passengers to seats). However, the dataset is limited to only scheduled passenger flights, and does not include charter, cargo or military operations or any ad hoc passenger flights.

Berster et al. (2011) uses an earlier OAG dataset (2008) in a study that explores the empirical relationship between annual air traffic movements and shorter-term peaks in demand, and this focuses on flights rather than measures of passenger demand. In contrast, the analyses in present study are based on seats, rather than passenger numbers. Passenger numbers (and load factors) are commercially sensitive and while they may be publicly available for specific airlines and airports, a decision was made to use seat data since this provides the widest coverage of airports.

The flights in the dataset are linked not only to an airport, but also to a terminal within the airport. For many airports there is a single terminal, but for larger airports there will more than one. The focus of this study is on terminal design so, unless otherwise indicated, results are for individual terminals.

### 2.2. Annual demand and Standard Busy Rate

The conventional ratio method is based on the relationship observed empirically between annual demands and the chosen short-term demand metric. In this paper we will use the annual number of seats and the number of seats in the 30th busy hour (i.e. the SBR), respectively, for these two quantities (though we show in Annex A, that there is a strong correlation between SBR and BHR measures). The results from the dataset are shown in Fig. 2.

While it is apparent that there is a broad correlation between annual demands and the short-term demands, there is structure associated with low to medium annual demands. This naturally arises from the lower limits that can be placed on the SBR, for a given annual demand. There are two obvious cases:

1. The lowest SBR, for a given annual demand, is where the flights are evenly distributed across all operational hours.

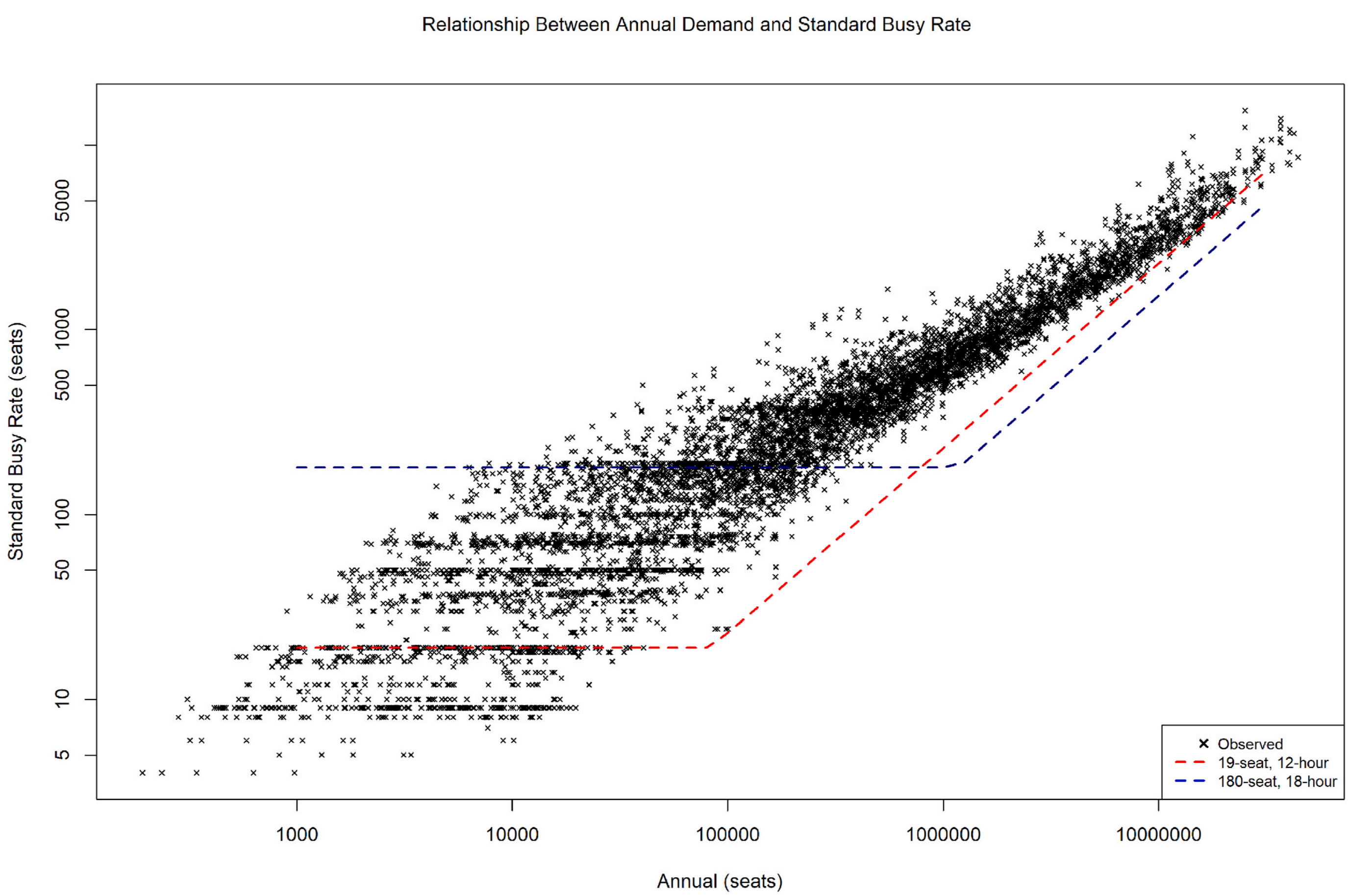


**Fig. 2.** Relationship between annual demand and standard busy rate.

2. In the case of low intensity operations (where in any given hour there is at most one flight) the SBR is simply the number of seats on the aircraft operating in that hour.

Thus, the lower limit on the annual seats to SBR seats relationship is

$$SBR \geq \max\{s_f, s_a / h_o\},$$

where $s_f$ is the number of seats on a flight, $s_a$ is the annual number of seats, and $h_o$ is the number of operating hours in a year. These lower limits, for two illustrative cases, are shown in Fig. 2: (a) a 19-seat aircraft with 12-h operational days ($h_o = 4{,}380$), and (b) a 180-seat aircraft with 18-h operational days ($h_o = 6{,}570$). The independence of SBR at lower annual demands is clearly seen and explicable: one flight per week or one flight per hour would both have the same number of seats in the busy hour, but the annual number of seats would vary by more than two orders of magnitude (i.e. 8760/52 = 168). In medium-/high-intensity operations (with annual seats above, say, 100,000), the smaller the number of operating hours the greater the minimum SBR.

#### 2.2.1. Power law relationship

A power law model can be fitted to the relationship between annual and short-term demands and this is the basis of the ratio method. From the preceding analysis, such a model cannot apply to low-intensity operations. However, taking a subset of the dataset, with terminals with annual seats numbers of 1,000,000 or more (1813 cases from the full dataset), a power-law model can be fitted with reasonable success (Fig. 3).

The empirical power law model for the larger airports is

$$\text{SBR} = 0.03\, s_a^{0.72} \tag{1}$$

The adjusted R-squared value is 0.8924.

This simple model is convenient for rough order of magnitude estimates. Nevertheless, for any given number of annual seats, the observed data is still widely spread.

#### 2.2.2. Poisson Model

The empirical power law relationship provides an estimate of typical values of SBR given annual demands. However, it provides only a single value and, while useful for scoping studies and early planning, it does not reflect the spread in observed values of SBR for any given annual demand. Furthermore, being empirical, there is no theoretical underpinning of why the relation between annual demands and SBR is what it is observed to be.

The power law model does not explicitly account for different operational hours at airports. Yet, as discussed previously, in the context of setting a lower limit on the SBR metric for a given number of annual seats, the number of operational hours must have a bearing on the SBR metric – an airport that compresses its flying schedule into 12 h may be expected to have a higher SBR than another airport with the same annual number of seats, but which spreads its flying schedule over 24 h. We propose an improved model which explicitly includes a measure of operational hours.

Without any additional insight it might be reasonable to assume that flights are assigned randomly to operating hours throughout that year. However, it is improbable that flights will be perfectly evenly distributed across all operating hours, and so too is it improbable that all flights will be lumped into the minimum number of very busy hours. We propose using a Poisson distribution for the random variable $X$ that denotes the number of flights in one operating hour. The probability mass function is

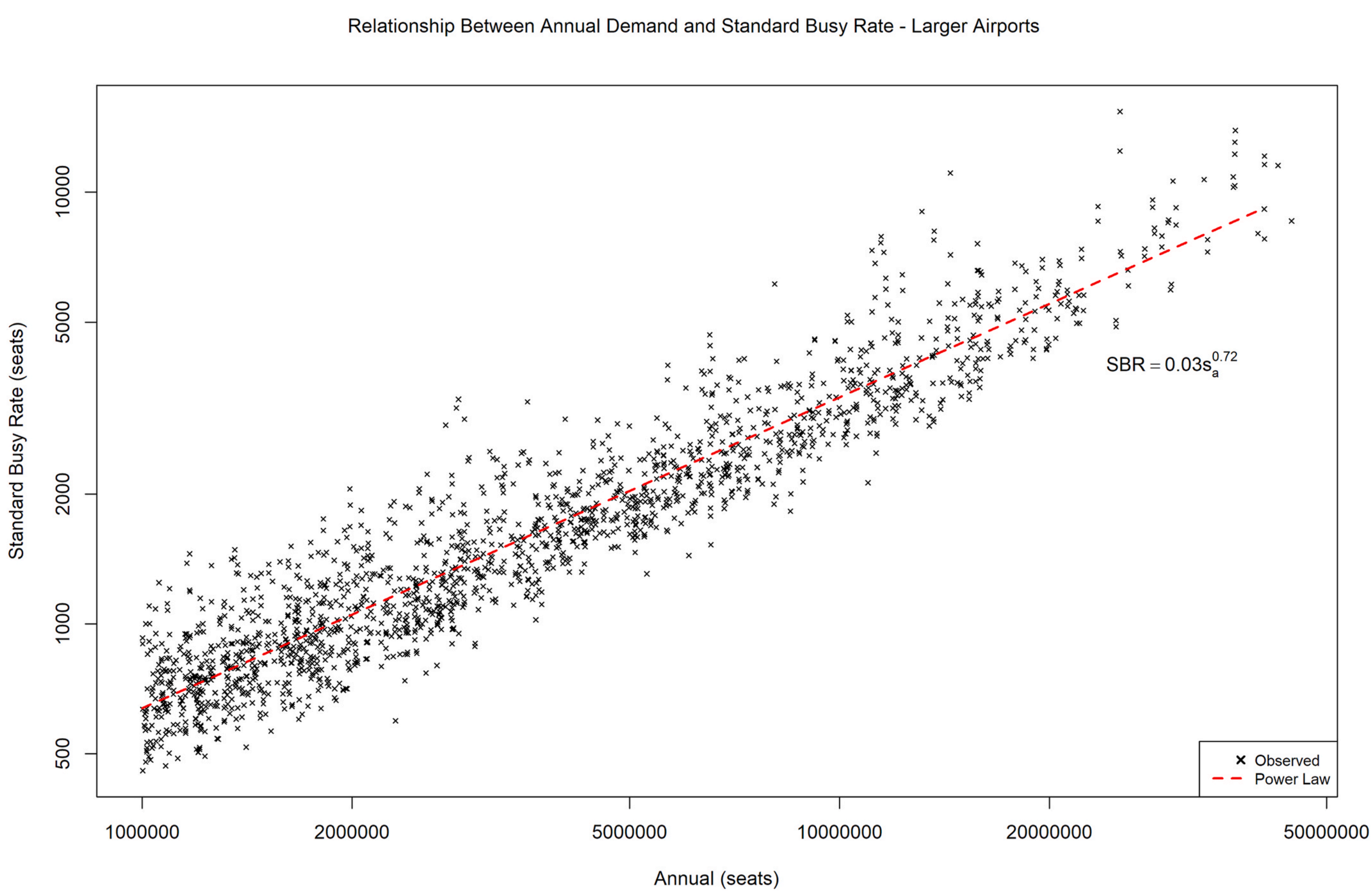


**Fig. 3.** Power law model for larger terminals.

$$\Pr(X = k) = p(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \quad k = 0, 1, 2, \ldots$$

where $\lambda$ is the mean number of flights per operational hour and $p(k;\lambda)$ is the probability of $k$ flights occurring in a 1-h window. The value of $\lambda$ is calculated from the annual number of flights, $f_a$, and the actual number of operating hours in a year $h_o$, as follows:

$$\lambda = \frac{f_a}{h_o}.$$

The expected number of 1-h windows to be "used" (i.e. a 1-h window containing one or more flights), $N_{exp}$, from the Poisson model is

$$N_{exp} = h_o(1 - p(0;\lambda)) = h_o\left(1 - e^{-f_a/h_o}\right).$$

The actual number of used windows (taken from the dataset) and the expected number of used windows (from the Poisson model for a set of different values of $h_o$) are shown in Fig. 4. Additionally, two *upper* limits on the number of windows that could be used are also drawn. The first limit is simply 8,760, which is the maximum number of hours in a year. The second limit is the number of windows that would be used if the annual flights were so arranged that there was only one flight per window.

The family of Poisson model lines behave as expected at their limits. They also capture the transition from low-intensity to high-intensity operations well, with plausible values of operating day lengths covering many observed values. Obtaining an estimate of the *effective* operating hours is critical, and this is discussed in the following section.

### 2.2.3. Effective operating periods

The preceding section showed how a simple Poisson model of aircraft movements provides a plausible model of the number hourly windows used per year, given the total number of flights in a year and an assumption about the number of hours in a day in which at least one flight occurred. In this section we develop a method to calculate the "effective operating hours" which is more nuanced than simply counting windows with one or more flights.

The purpose of defining a measure of effective operating hours is to capture a period of time over which a substantial fraction of flights actually occurs. Here we must make a distinction between the period of time when an airport is open and the period of time during which flights are actually active. For example, an airport might be "open" from 8 a.m. until 10 p.m. (i.e. 14 h), but if, for example, there is one flight in the morning and one flight on the afternoon, then the airport is, in effect, operating for just 2 h a day. A simple definition of effective operating hours would be the number of windows used (i.e. actual operating hours, meaning the number of hours in which one or more flights occur, as used in section 2.2.2. However, there is a further factor to be considered, namely the intensity with which slots are used. For instance, take a case when an airport has at least one flight in each of 18 h in a day. Using the definition above, the actual operational day would be 18 h. If there were simply 18 flights, one in each operational hour, then 18 h would be a fair reflection of the period over which a substantial fraction of the flights occurred. But consider an alternative scenario in which the airport also has 18 h in which at least one flight operates, but for 17 h there is one flight in each hour while, in the remaining single hour, 50 flights operate. As before there are 18 slots in which one or more flights operate, but for practical purposes, most of the flights take place in 1 h. When looking at peak demands, the *effective* operating hours are closer to one than 18. We propose the following method to provide a measure of the effective operating hours.

Fig. 5 shows three hypothetical profiles of flights over the course of a 24-h period. In the first case, each hour has the same number of flights in

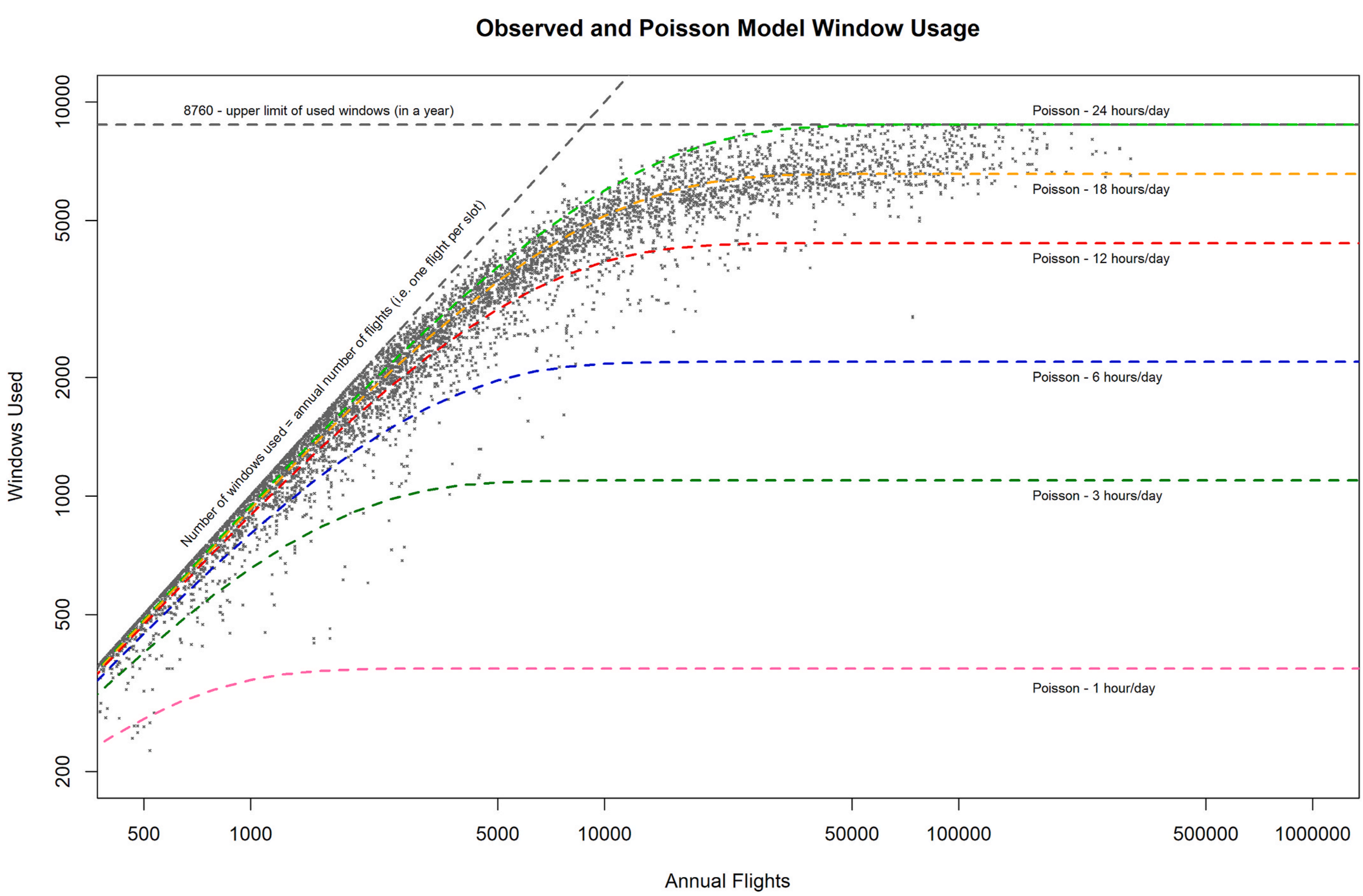


**Fig. 4.** Observed and Poisson model window usage.

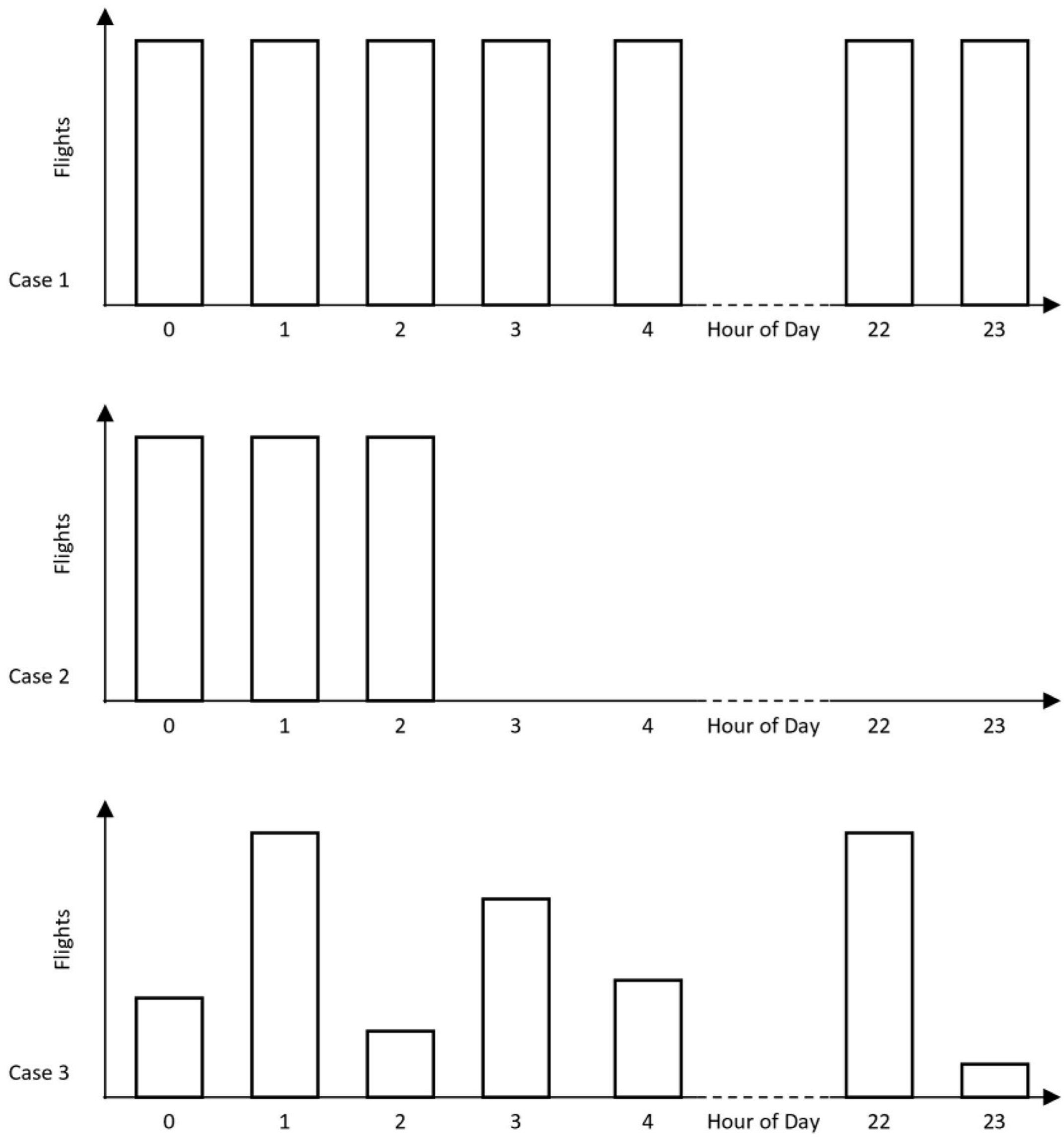


**Fig. 5.** Flight profiles.

each of the 24 h. In the second case, there are just 3 h which have flights (each active hour having the same number of flights). Moreover, the third case represents an arbitrary profile, with a variety of numbers of flights in each hour. Using the earlier, simple, definition of actual operating hours, Case 1 would be 24 h, Case 2 would be 3 h, and Case 3 would be 24 h if there was at least one flight in each hour throughout the day, but there would be only seven operating hours if none of the hours not shown (i.e. 5-21) had a flight. However, while Case 1 is evidently a 24-h operation by any measure, Case 3 may be a 24-h operation, but most flights fall within a smaller number of hours. It is this unevenness or peakiness that the following method seeks to capture.

The approach is to calculate the coefficient of variation of the number of flights by hour. Let the number of flights in a 1-h period be denoted by the random variable $X$. Consider the special case in which there are $m$ periods out of a total of $n$ and in which each active period has the *same* number of flights (in Case 1 $m = 24$ and $n = 24$, and in Case 2 $m = 3$ and $n = 24$). The population of $X$ we consider is $x_1, \ldots, x_n$. The population variance is given by:

$$\mathrm{Var}(X) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2.$$

If $x_i = n/m$ for $i \leq m$, and $x_i = 0$ for $i > m$, then $\overline{x} = 1$, and so:

$$\mathrm{Var}(X) = \frac{n}{m} - 1.$$

($x_i$ can be any fixed number without loss of generality, but by choosing it to be $n/m$ the mean number of flights, $\overline{x}$, is 1.)

Therefore, the coefficient of variation, $c$, is given by:

$$c = \sqrt{\frac{n}{m} - 1}. \tag{2}$$

In Case 1, with $m = n$, gives $c = 0$, while Case 2, with $m = 3$ and $n = 24$, gives $c = 2.65$. Re-arranging Equation (2) to express $m$ in terms of $n$ and $c$ produces:

$$m = \frac{n}{c^2 + 1}. \tag{3}$$

This means that, given calculated or observed values of $c$ and a value for $n$, an estimate of $m$ can be made. Therefore, in Case 3, if the value of $c$ is obtained, the effective number of hours, $m$, from a total of $n = 24$ hours can be calculated. There is no reason why $n$ and $m$ should refer just to hours of the day. They could be applied to days of the week (i.e. $m$ days out of 7) or weeks of the year (i.e. $m$ weeks out of 52). Thus, we have metrics of seasonality, the pattern of the working week, and intra-day schedule factors, as will be explained below.

*2.2.4. Observed effective operating periods*

As introduced before, the variation of flights over three different timescales can be measured from the dataset. The timescales used in this study were:

1. Number of weeks per year – a proxy for “seasonality factors”;
2. Number of days per week – a proxy for “business/cultural factors”;
3. Number of hours per day – a proxy for “schedule factors”.

The number of months per year would have been an alternative for the first timescale. But, as observed by Matthews (1995), in his analysis of the variation of demands at Heathrow (and other BAA-owned airports), there are an unequal number of days in each month which would complicate the calculation.

The benefit of describing variation in terms of weeks per year, days per week, etc., is that it is more accessible to a range of stakeholders (planners, managers, and investors) than, say, coefficients of variation.

For each airport, terminal, and arrive/depart direction, the number of flights in a given week number (or day of week, or hour of day, for the other timescales) is determined. Then the population standard deviation of the numbers of flights and the mean number of flights in each week (or day of week, or hour of day) are calculated. (Note that care was taken to include periods in which no flights were recorded in the calculation of standard deviations and means.) The coefficient of variation $c$ is first calculated and then converted into an effective number of periods $m$, given the total number of periods $n$, using Equation (3) ($n = 52$ for weeks in a year, $n = 7$ for days in a week, and $n = 24$ for hours in a day).

The dataset has a large range of different numbers of flights per year. The minimum was 30 and the maximum was 306,050 – covering four orders of magnitude. Given this large range of different scales, the analysis of effective weeks, days, and hours was split into five logarithmically spaced segments, based on annual numbers of flights: 1 to 10, 10 to 100, 100 to 1,000, etc. We refer to these five segments as follows: low (10–100 flights), low-to-medium (100–1000 flights), medium (1000–10,000 flights), medium-to-high (10,000 to 100,000 flights), and high intensity (more than 100,000 flights). Histograms of the number of weeks (rounded to the nearest whole number) per year (and similarly days per week and hours per day) were created for each segment (see Fig. 6).

At the lowest level of intensity, there is a wide range of effective operational weeks per year, and operational days per week – in both cases the majority of operations are well below 52 weeks and 7 days, respectively. At low-to-medium intensity there is still a wide range in numbers of operational weeks (and operational days), with most airports operating less than 52 weeks a year and 7 days a week. At medium intensity, the majority of airports operate at least 51 weeks a year and 7 days a week, though there are still cases where weekly and daily operations are less frequent. For medium-to-high intensity the same trend continues, though there are still cases where there are fewer than 50 operational weeks per year. In contrast, virtually all airports operate 7 days per week. Finally, for high intensity operations, most airports operate 52 weeks per year and 7 days a per week.

The distribution of the effective number of hours per day changes as the intensity increases. The mode of the number of hours per day moves from 1 (for low intensity) to 17 and 18 (for high intensity). At all intensities there is an appreciable spread skewed to lower numbers of hours in low to medium intensities, becoming roughly symmetrical for

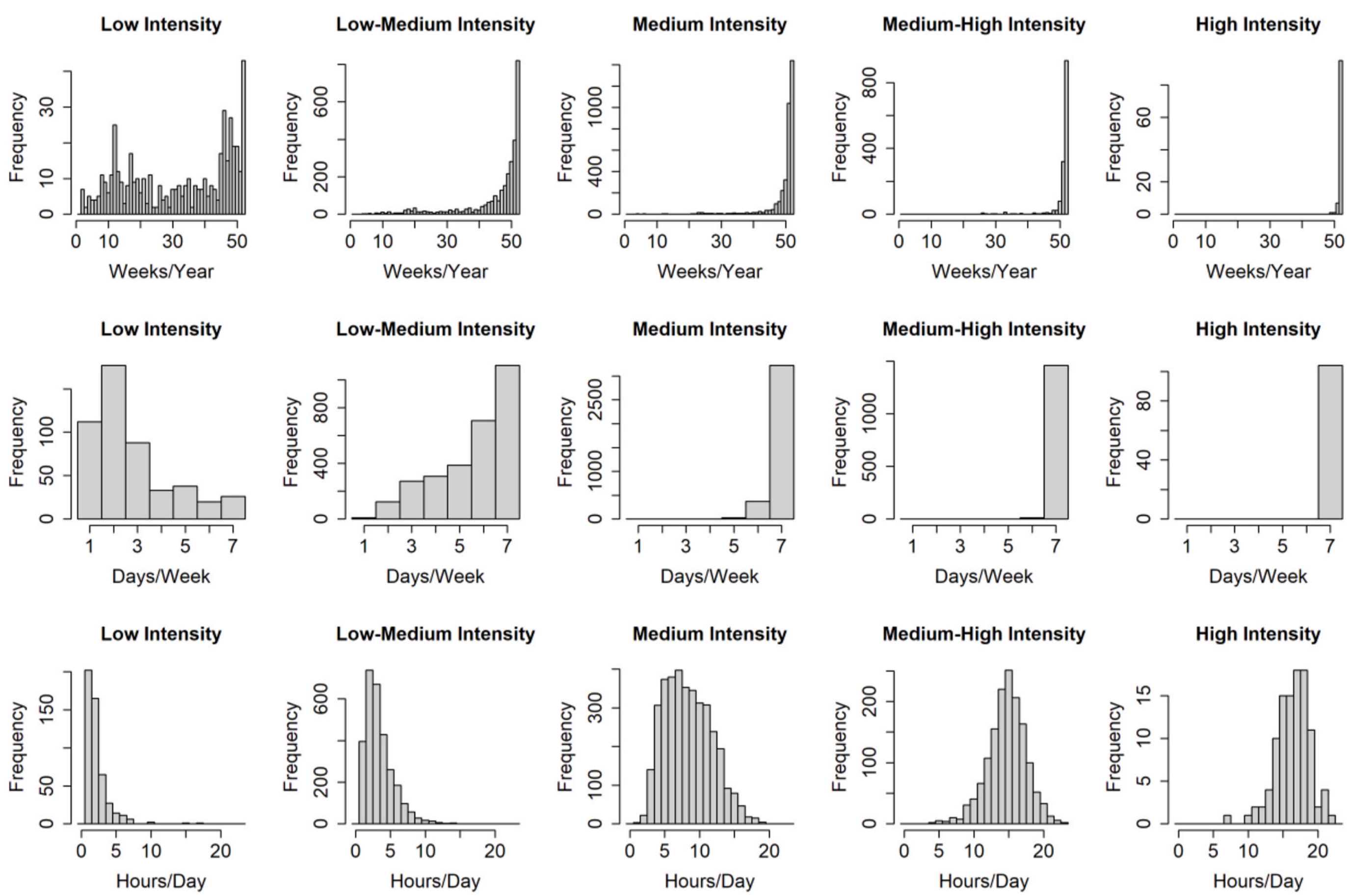


**Fig. 6.** Effective weeks, days, and hours distributions.

medium-to-high intensity, and finally become somewhat skewed to the right for high intensity – though there are still relatively few airports with 20 or more effective operational hours even at this level of intensity.

These graphs alone can provide useful context in the development of the design basis for a new airport or terminal, by indicating the likely range of parameter values that might be expected to apply.

### 2.3. Poisson Model estimate of window usage

Fig. 4 shows the number of 1-h windows used in a year and provides *upper* limits on the number that could be used. A number of profiles based on a Poisson model showed the expected number of slots that could be used, based on assumptions about operating hours. Now that we have a means of calculating effective operating hours, Fig. 7 plots the observed data against three Poisson model curves. The individual points show the annual number of flights (x-axis) and the actual number of slots used (y-axis). In the case of the left-hand graph, observed cases where the effective operating hours are between 17 and 19 h have been plotted and the Poisson model assuming 18 h has been drawn. The other graphs show data with effective operating hours of between 11 and 13 h with a Poisson model assuming 12 h, and effective operating hours of between 5 and 7 h with a Poisson model assuming 6 h. The Poisson model curves provide a *lower* limit on the number of slots used.

### 2.4. Revised model of Standard Busy Rate

Having defined a measure of the effective number of operating hours, this can used with the Poisson model to compare its estimate of the SBR with what was actually observed.

The procedure is as follows:

1. Calculate the effective operational hours in a year, by multiplying effective weeks per year, effective days per week, and effective hours per day for each airport/terminal.
2. Divide the annual number of flights by the effective operational hours per year to find the mean number of flights λ, per effective operational hour.
3. Find the number of flights corresponding to the 8730/8760 = 99.54%-ile of the Poisson distribution, *p*, with mean λ (i.e. the 30th busy hour).
4. Multiple the number of flights by the average number of seats per aircraft, *N*, to obtain an estimate of the SBR.

In terms of implementation, using R, this is achieved using Equation 4, where qpois is the quantile function for the Poisson distribution (R Core Team, 2022).

$$\mathrm{SBR} = N \times \mathrm{qpois}(p, \lambda)\ . \tag{4}$$

Fig. 8 shows the results arising from the power law model (left) and the Poisson model (right). In each case, the x-axis indicates the actual SBR for a given terminal and the y-axis shows the estimated SBR from each model. It is evident that the power law model's results show greater dispersion than the Poisson model's results. The standard error of the power law model is 692 seats, while that of the Poisson model is 452 seats. This is borne out by a comparison of the relative errors of two models (see Fig. 9).

While both models achieve around 70% of results with a relative error of 20% or less, the Poisson model is notably better at avoiding much larger errors than the power law model (see Table 3).

The other advantage of the Poisson model is that it does not rely on historical data (unlike the power law) – it can be obtained from first principles with simple assumptions.

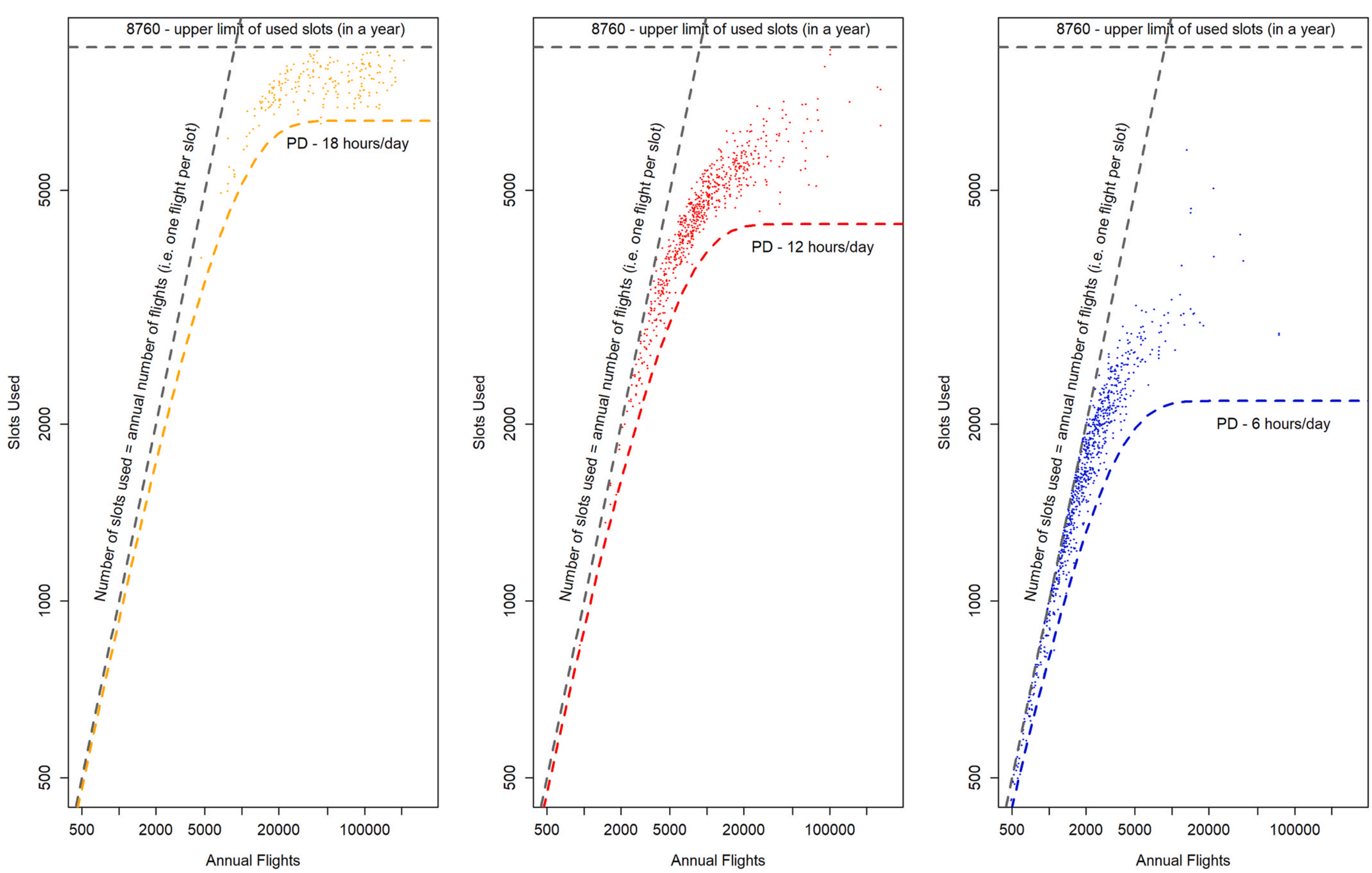


**Fig. 7.** Poisson model and window usage limits.

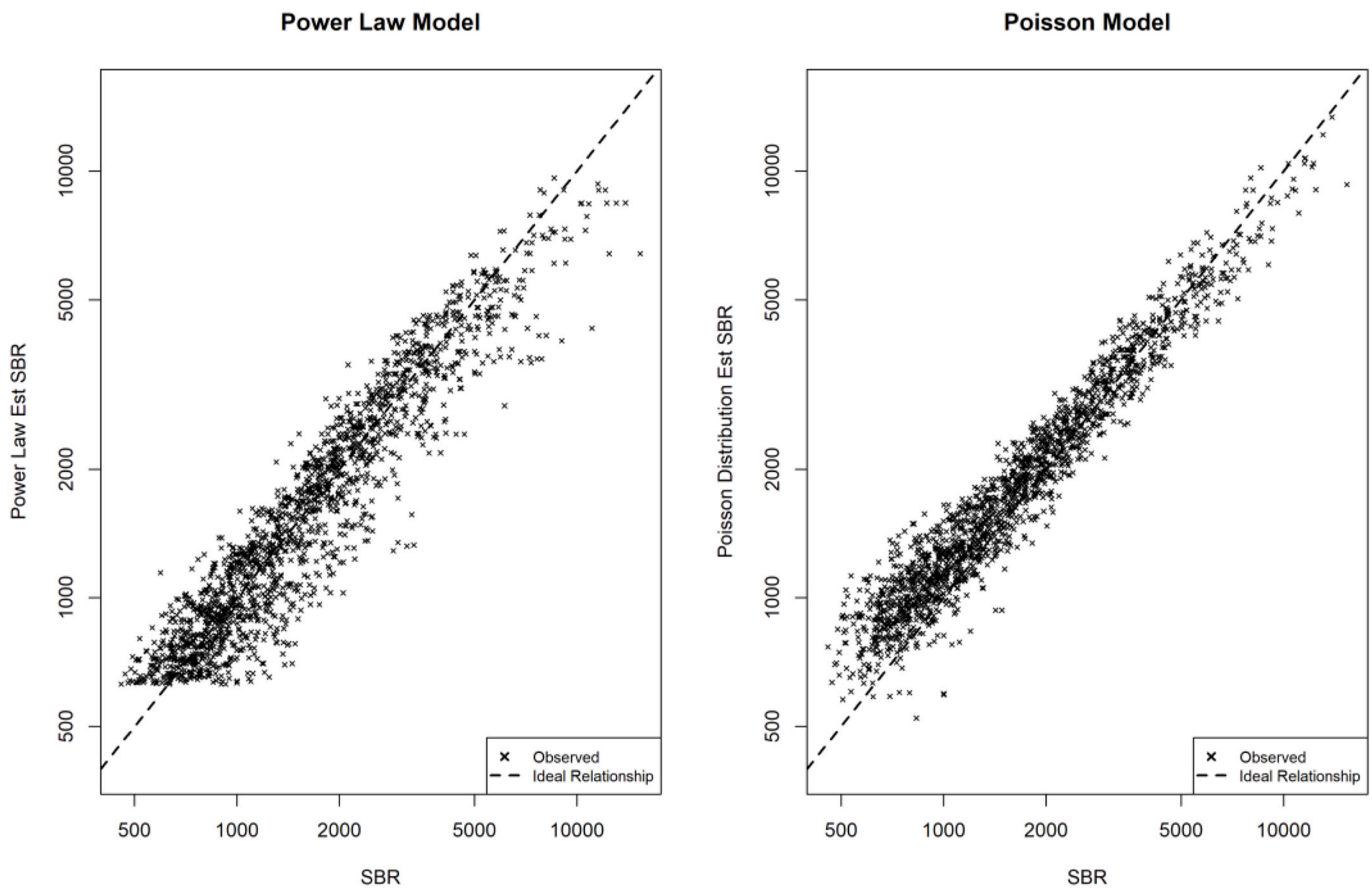


**Fig. 8.** SBR estimates – models compared.

## 3. Case study: application to a design workflow

In this section, we consider a typical design workflow and show how the proposed parametric method complements and enriches conventional methods.

We take, as an example, how the design basis for a proposed new European hub airport and terminal (we refer to it as Terminal X), was defined. Six different design day schedules were produced covering a period from the late 2020's to 2100. For this study, we select the schedule for mid-2040's. Each schedule reflects a single "peak" day's operation in the nominal year. Also, for each schedule year, the number of annual passengers is quoted as a business assumption.

Key values taken from the selected design day schedule are given in Table 4. From this, two factors can be derived:

1. Peak day seat factor = 197,186/227,438 = 0.867.
2. Peak day average seats per flight = 227,438/1218 = 187.

One might conclude that the number of passengers departing in the peak hour is c. 11,279, though for this analysis, rather than using passenger numbers, we will simply use peak hour seat numbers which, in this case, is 12,424 departing seats in the peak hour. However, a Standard Busy Rate or a Busy Hour Rate cannot be calculated from the design day schedule, because both these measures depend on a knowledge of all other hourly demands across a whole year. The risk, therefore, is that the design day schedule demands are, in fact, absolute peak demands. The consequence of this is that the terminal's infrastructure may be over-engineered, thereby adding unnecessary costs. The proposed parametric method is intended to challenge this type of single point estimate by (a) estimating an SBR value rather than an absolute peak value and (b) allowing observed patterns of "peakiness" to be applied to create a range of plausible SBR values with probabilities.

First, we seek to find in the observed data other terminals which are "similar" to Terminal X in terms of (a) maximum number of seats per day and (b) number of days of this peak that would equal the annual number of seats. The first factor is a measure of the size of demand, and the second factor is a measure of the peakiness of the demand throughout the year.

Ideally the number of seats per year would be provided directly as part of the design day schedule but this was not the case for Terminal X. We therefore must estimate the annual number of seats, given the peak number of seats. In this case, if the seat factor were assumed to be achieved throughout the year, then 25 million departing (or arriving) passengers would require 25/0.867 = 28.8 million seats. (Note that this is equivalent to saying that the annual demand would be numerically equal to about 252 peak days.) However, seat factors are generally not maintained at the peak level throughout a year, so this would represent a lower limit on the number of seats.

Fig. 10 shows the relationship between annual numbers of seats and peak day numbers of seats for terminals with one million or more seats per year, taken from the dataset. A linear regression model (constrained to pass through the origin) is also shown. This gives:

$$s_{pd} = 3263 \times s_a.$$

where $s_{pd}$ is the number of seats in the peak day, and $s_a$ is the annual number of seats (expressed in millions). The adjusted R-squared is 0.971, and the standard error is 4702 seats.

Thus, for the example case, an estimate of annual seats from the peak day number of seats (113,861) would be 34.9 million seats. (Note that this is equivalent to stating that the annual demand would be numerically equal to about 307 peak days.) This is shown in Fig. 11 along with the results for the 20 most similar demands (in terms of peak day seats,

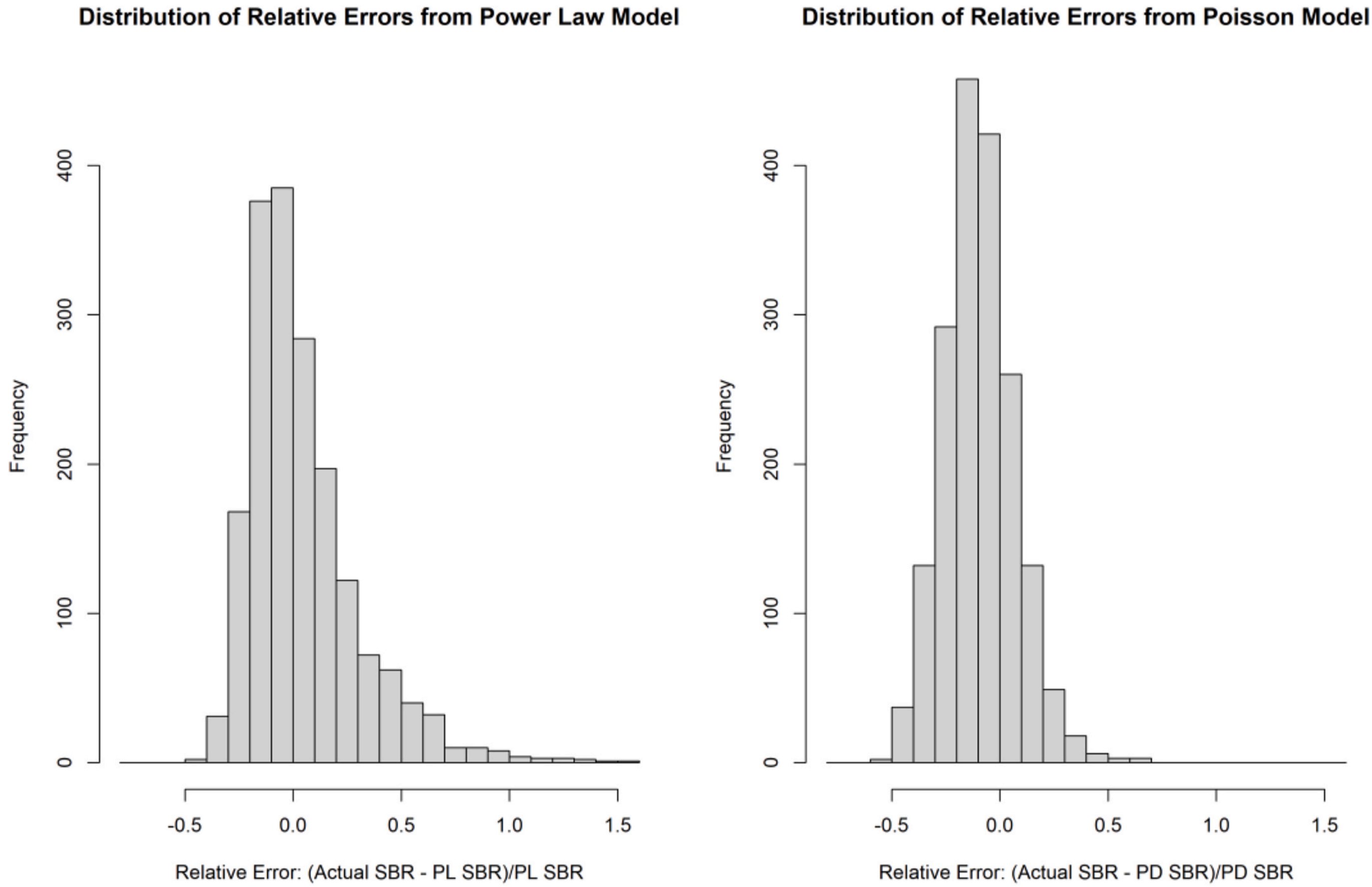


**Fig. 9.** Distribution of relative errors – models compared.

**Table 3**
Fraction of results within relative error ranges.

| Relative Error | **Number (PL)** | **Percentage (PL)** | **Number (PD)** | **Percentage (PD)** |
|---|---|---|---|---|
| **±0.1** | 669 | 36.9% | 681 | 37.6% |
| **±0.2** | 1242 | 68.5% | 1271 | 70.1% |
| **±0.3** | 1532 | 84.5% | 1612 | 88.9% |
| **±0.4** | 1635 | 90.2% | 1762 | 97.1% |
| **±0.5** | 1699 | 93.7% | 1805 | 99.6% |
| | 1813 | 100.0% | 1813 | 100.0% |

**Table 4**
204X design day schedule – key values.

| | Pax/ year | Seats/ day | Pax/ day | Flights/ day | Peak hour/ seats | Peak hour/ flights |
|---|---|---|---|---|---|---|
| **Arr** | 25 million | 113,861 | 98,744 | 610 | 12,424 | 67 |
| **Dep** | 25 million | 113,577 | 98,442 | 608 | 13,009 | 72 |
| **Total** | 50 million | 227,438 | 197,186 | 1218 | n/a | n/a |

while excluding any cases in which there would be fewer than 252 peak days, since these would be infeasible). The airport codes are explained in Table 5.

While the regression result lies within a range of observed results, the majority of observed results are less peaky in that they have more peak day equivalents per year. Particularly referring to other European hubs (FRA and AMS), 320–330 days would be a more plausible value for Terminal X. Indeed, the median of these 20 observations is 332 days. We use this to estimate the annual number of seats, which yields 36.7 million seats.

Having estimated the annual number of seats the first estimate of the SBR can be made using the power law model. Using the median value of 36.7 million seats in (1) gives a power law model estimate for the SBR of 8400 seats. We do not attach too much significance to this figure because the power law model represents an average across many terminals each with different levels of within-day peakiness. Nevertheless, the value is lower than the design day schedule's peak number of seats which is to be expected.

We now apply the Poisson model which uses an additional parameter to represent the effective number of hours of operation. Fig. 12 shows the pattern of arriving flights in the example design day schedule. The coefficient of variation for this profile is found to be 0.789 which, using (3), can be interpreted as an effective day of 14.79 h.

The number of effective hours per day is a key metric reflecting the peakiness of the flight schedule. For the largest terminals (that is, the High Intensity cases in Fig. 6), the within day variability is much greater than either the day of the week, or the week of the year variability. The effective numbers of hours per day for the 20 "most similar" terminals (as defined above) are shown in Fig. 13. From this, we observe that Terminal X (at 14.79 h) is "similar" to FRA, another European hub airport, suggesting that the peakiness of the design day schedule is plausible. However, it remains the case that 75% of observed cases have less peaky daily profiles, as measured by the effective hours metric.

The number of effective hours per day is used in the Poisson model to estimate the seat SBR by the process set out in Section 2.4. In this case, we use the data for the single design day: 610 arriving flights over 14.79 h giving a value for $\lambda$ of 41.5 flights per hour, an average number of seats per flights, $N$, of 186.7, and $p = 8,730/8,760$ as the ratio to represent

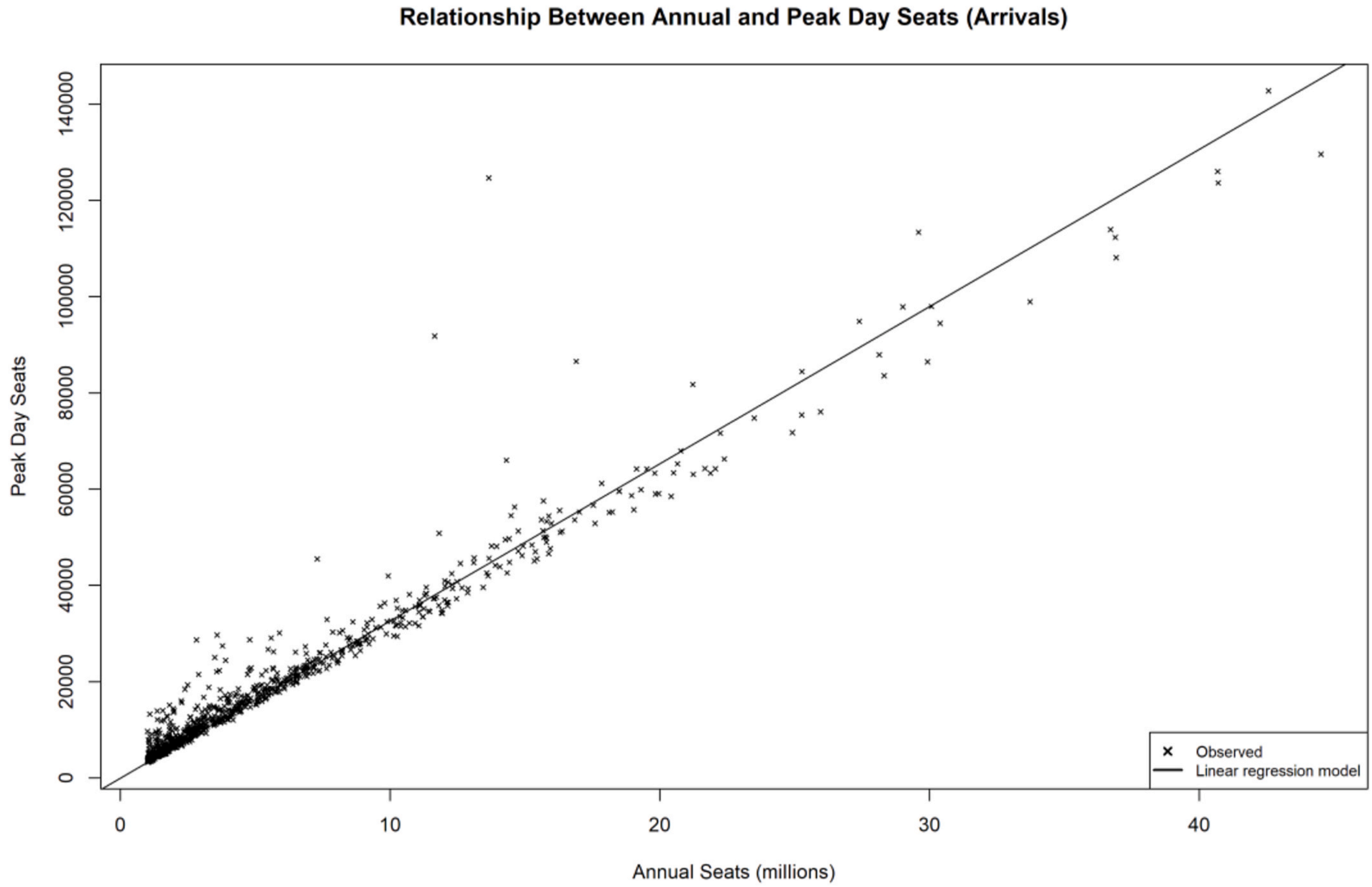


**Fig. 10.** Relationship between annual and peak day seats (arrivals).

the 30th busiest hour in a year. This gives an estimate of 60 arriving flights in the 30th busiest hour, and 11,202 seats for the estimated SBR.

The SBR values for the most "similar" 20 terminals are shown in Fig. 14. Also shown are three different estimates of the SBR for Terminal X. The first is the peak number of seats arriving in an hour taken from the design day schedule: 12,424. This is likely to be an overestimate since the value is taken from the busiest single day, rather than using a concept of the 30th busy hour. The power law model value, based on an estimate of the annual seats, is 8400 seats. Since this model takes no account of effective hours in a day and, because of the relatively low number of effective hours in the case of Terminal X, it is likely to underestimate the SBR. The Poisson model estimate falls between these two extremes lying close to the FRA results, which is similar in terms of both size and nature of operation.

The design day schedule, when analysed, produces a peak hour arriving demand of 12,424 seats. However, this value has little context and is not linked to any traditional concept of SBR or BHR. One can appeal to the power laws result of between 7181 and 8830 seats (with a median value of 8400 seats) based on other terminals of a similar estimated size to estimate the SBR, but the power law does not include any impact of the effective operating day length. Consequently, while it might suggest that the design basis is larger than might otherwise be expected, this alone is not persuasive.

The effective day length metric is calculated from the hourly arrival pattern taken from the design day schedule and found to be 14.78 h. This, together with the number of arriving aircraft in the design day schedule, and the average size of the aircraft (187 seats) is used to estimate the SBR using the Poisson model. The result obtained is 11,202 seats. Basing a design on this figure would result in a headline saving of c. 10%, compared with the design day schedule peak demand.

The foregoing analysis is based on an assumption that the effective day for Terminal X actually proves to be 14.78 h. This value is "baked in" to the design day schedule. But what if we wish to see the effect of different values? By using the historical data on effective operating hours per day for High Intensity terminals (see Fig. 6) we can fit a beta distribution which describes reasonably well the observed profile (see Fig. 15).

Using the fitted beta distribution as a representation of the actual distribution of effective hours we calculate the SBR values for Terminal X (i.e. 187 seats per aircraft and 36.9 million seats per year) with different effective hours per day and associated probabilities, using the Poisson model.

The results are shown in Fig. 16, which plots the probability that a given SBR value will be exceeded, for the case of 34.9 million seats per year. It indicates that an SBR rate of more than c. 11,000 is most improbable, again providing an indication that the peak demand arising from the design day schedule should be critically questioned. Indeed, an SBR value of closer to 10,000 might be judged as being more likely – a reduction in the design basis of around 20%. The effect of uncertainty in forecasting annual passenger numbers on the SBR can also be included in the proposed method simply by applying a range of forecast annual values to the calculation of λ used in (4). Then, instead of a single line, a family of lines (one for each annual forecast) is produced. We show this for additional cases of 30 million and 40 million seats per year (see also Fig. 16).

The rough order of magnitude of capital savings that this might imply can be estimated from the capital costs of delivering two airport projects: Terminal 5 at Heathrow (Wolstenholme et al., 2008) and Incheon Airport in South Korea (Lee, 2008), and their scale (as measured by annual passenger numbers in the early years of their respective operations).

In the context of the case study for Terminal X, a saving of 10%–20%

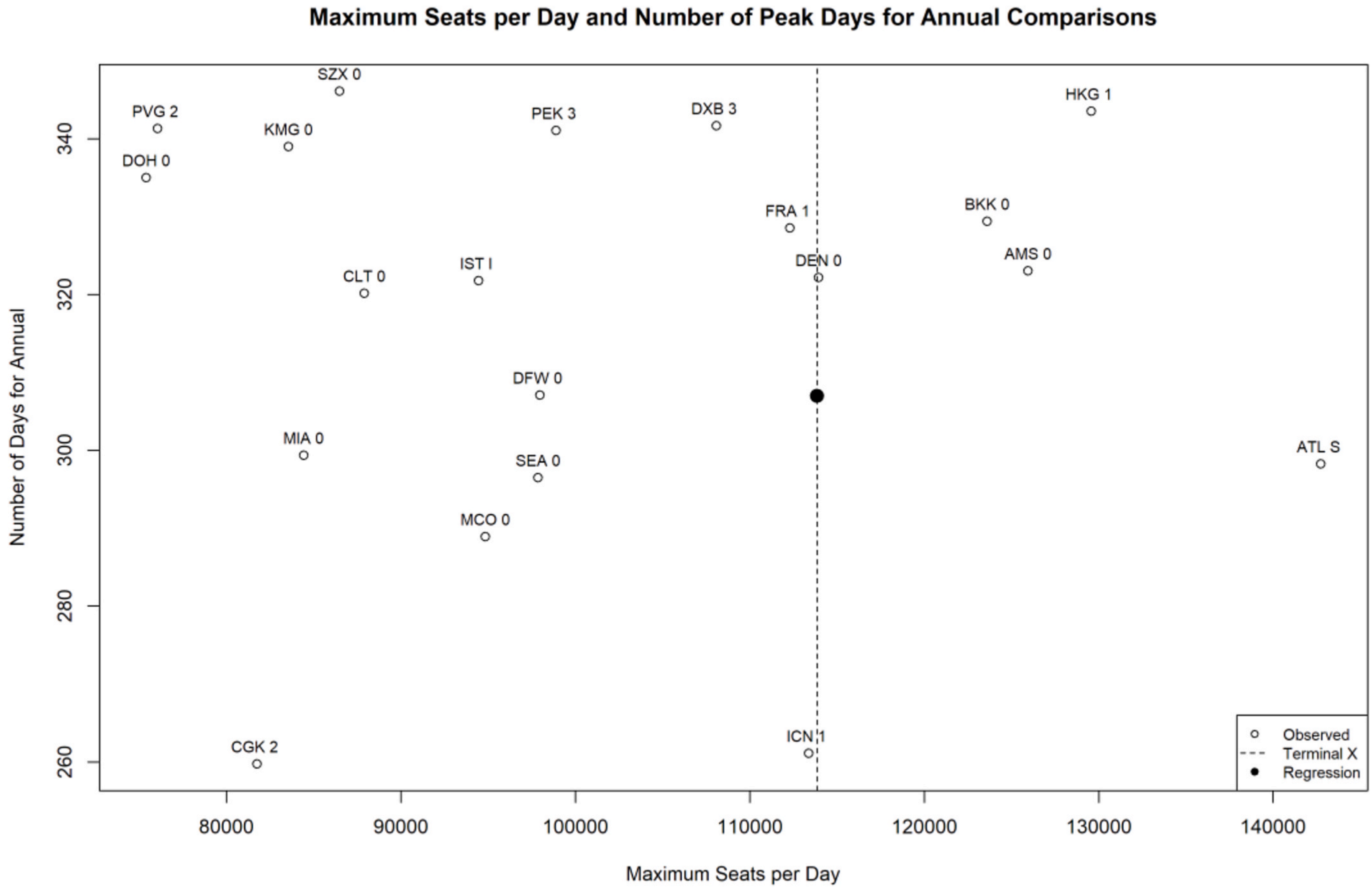


**Fig. 11.** Maximum seats per day and peak days for annual comparisons.

**Table 5**
Airport codes, names, and locations.

| Airport | Name | City | Country |
|---|---|---|---|
| AMS | Schiphol | Amsterdam | Netherlands |
| ATL | Hartsfield Jackson Atlanta Intl | Atlanta | United States |
| BKK | Suvarnabhumi Intl | Bangkok | Thailand |
| CGK | Soekarno Hatta Intl | Jakarta | Indonesia |
| CLT | Charlotte Douglas Intl | Charlotte | United States |
| DEN | Denver Intl | Denver | United States |
| DFW | Dallas Fort Worth Intl | Dallas-Fort Worth | United States |
| DOH | Doha Intl | Doha | Qatar |
| DXB | Dubai Intl | Dubai | United Arab Emirates |
| FRA | Frankfurt Main | Frankfurt | Germany |
| HKG | Hong Kong Intl | Hong Kong | Hong Kong |
| ICN | Incheon Intl | Seoul | South Korea |
| IST | Ataturk | Istanbul | Turkey |
| KMG | Kunming Changshui Intl | Kunming | China |
| MCO | Orlando Intl | Orlando | United States |
| MIA | Miami Intl | Miami | United States |
| PEK | Capital Intl | Beijing | China |
| PVG | Pudong | Shanghai | China |
| SEA | Seattle Tacoma Intl | Seattle | United States |
| SZX | Baoan Intl | Shenzhen | China |

(based on annual passenger numbers of c. 50 million) would, if scaled from the data in Table 6, be in the order of several hundreds of millions of dollars, suggesting that the ability constructively to challenge the design day schedule demands could have a material benefit in terms of capital cost. In a later stage of the case study project, the design basis was indeed reassessed and resulted in a lower peak demand, with a consequential reduction in the anticipated capital cost.

## 4. Discussion

The construction of a new passenger terminal at an airport can represent a large capital investment and therefore even relatively small changes in the design basis can have a large impact on the absolute cost.

The design basis is determined by the processing demands that occur over a short period of time, typically an hour or less. However, the business case is generally based on projected annual demands. Bridging these two perspectives is a key step in setting out the design requirements.

While the academic literature offers a number of different metrics for short-term demands (e.g. BHR, SBR, TPHP) and discusses their individual merits, all these measures, in theory at least, depend upon having an annual dataset from which the busy hour is selected according to the chosen method. In the case of a new terminal or airport, this historical data is not necessarily available. Indeed, new airports and terminals are often conceived to handle entirely new levels of traffic and patterns of demand. As the case study shows, the only demand data comes from a single-day forecast schedule with no context to determine how the peak hour (deduced from the design day schedule) is likely to compare with the chosen short-term demand metric.

The use of a ratio method, in which historically observed ratios of short-term demands to annual demands, offers a basic method of providing some context. However, basic ratio methods do not account for different patterns of traffic and, as shown, this can lead to large errors between the "model" and what was actually observed. In this paper, a refinement is proposed in which variations in demand over three different timescales (week of year, day of week, and hour of day) are captured by simple parameters that are readily understood by a wide

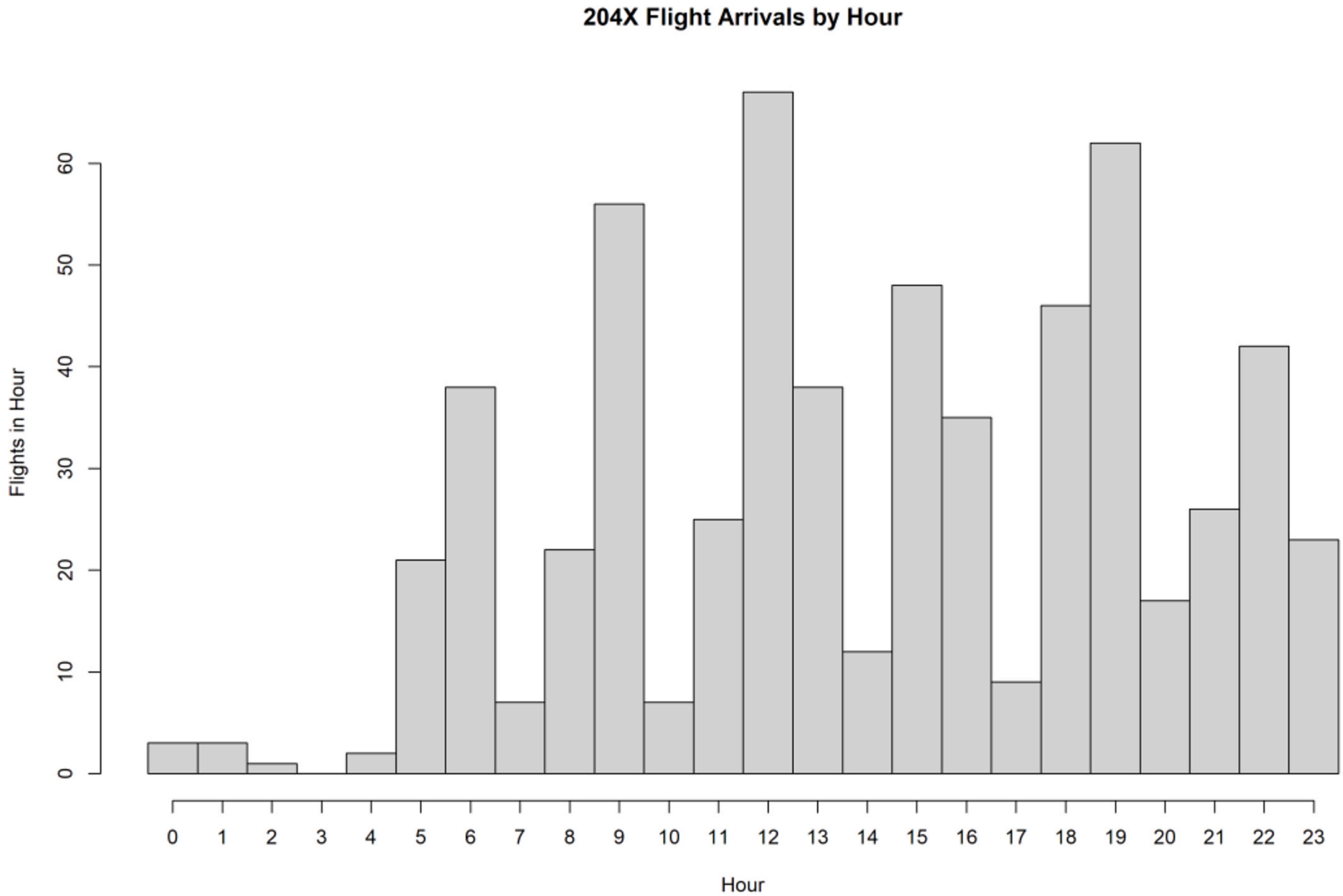


**Fig. 12.** Histogram of flight arrivals by hour from design day schedule.

range of stakeholders. The development of a Poisson model, which explicitly includes a measure of the peakiness of the flight schedule, allows the possibility of "what-if" studies without the development of new design day schedules. For example, the impact of a different profile as expressed by the effective number of hours per day is readily calculated. By placing key design figures (effective hours per day, SBR, etc) in the context of the global historical dataset, it becomes possible for decision-makers and designers to check the plausibility of the design basis assumptions and, where appropriate, challenge these early on in the design process. In the case study example, there are grounds for arguing that the design basis is somewhat too demanding, and this would, if accepted and reduced, lead to capital savings of as much as several hundred million dollars.

The forecasting of even annual demands is inevitably error prone. Near-term extrapolations are more likely to prove accurate, but longer-term air traffic forecasts are shown in the literature to have large errors and/or wide confidence limits. Thus, the use of a single design day schedule should be regarded as a useful data point, but it should be coupled with other benchmarks to provide context of what the range of plausible demands might be. The fact that a design day schedule has been painstakingly constructed does not mean that it is "right", and the adoption of complementary methods, such as the parametric method described in this paper, can provide the basis of a healthy challenge and review process to allow stakeholders to understand more clearly the plausibility of the design basis.

## 5. Conclusion

The acknowledged difficulties of either a simple ratio method or a design day schedule method have not prevented their use in practical airport terminal design applications. The proposed parametric method is no panacea, but it does offer a complementary method that is accessible to decision-makers, and which enables the design basis demands to be critically assessed early in the terminal development process. By challenging possibly over-stated demands, material savings in the capital cost of the development project may be achieved.

### 5.1. Limitations

There are a number of areas in which the method could be improved. The use of passenger data (rather than seat data) would be advantageous, though its availability is more limited, because of commercial considerations and, in some cases, the granularity with which it is reported. For computational ease, hourly data based on clock hours is used in this paper, although an obvious refinement would be to use rolling hours.

### 5.2. Future research

The combination of a large dataset, the need to represent results graphically, and the desire to be able to interact with the data with stakeholders in real time could all be supported with modern business intelligence tools. The development of such a tool is a possible next step.

We have focussed on 1 h time windows to specify the "peak" demands to be designed for. However, as service standards have developed and improved, demands occurring over even shorter time scales become more relevant: if targets for queue waiting times are in the order of 5–15 min, for example, then "peak" demands must reflect these shorter characteristic times. While we expect the Poisson model to be even more appropriate for shorter timescales, this is an area for further research.

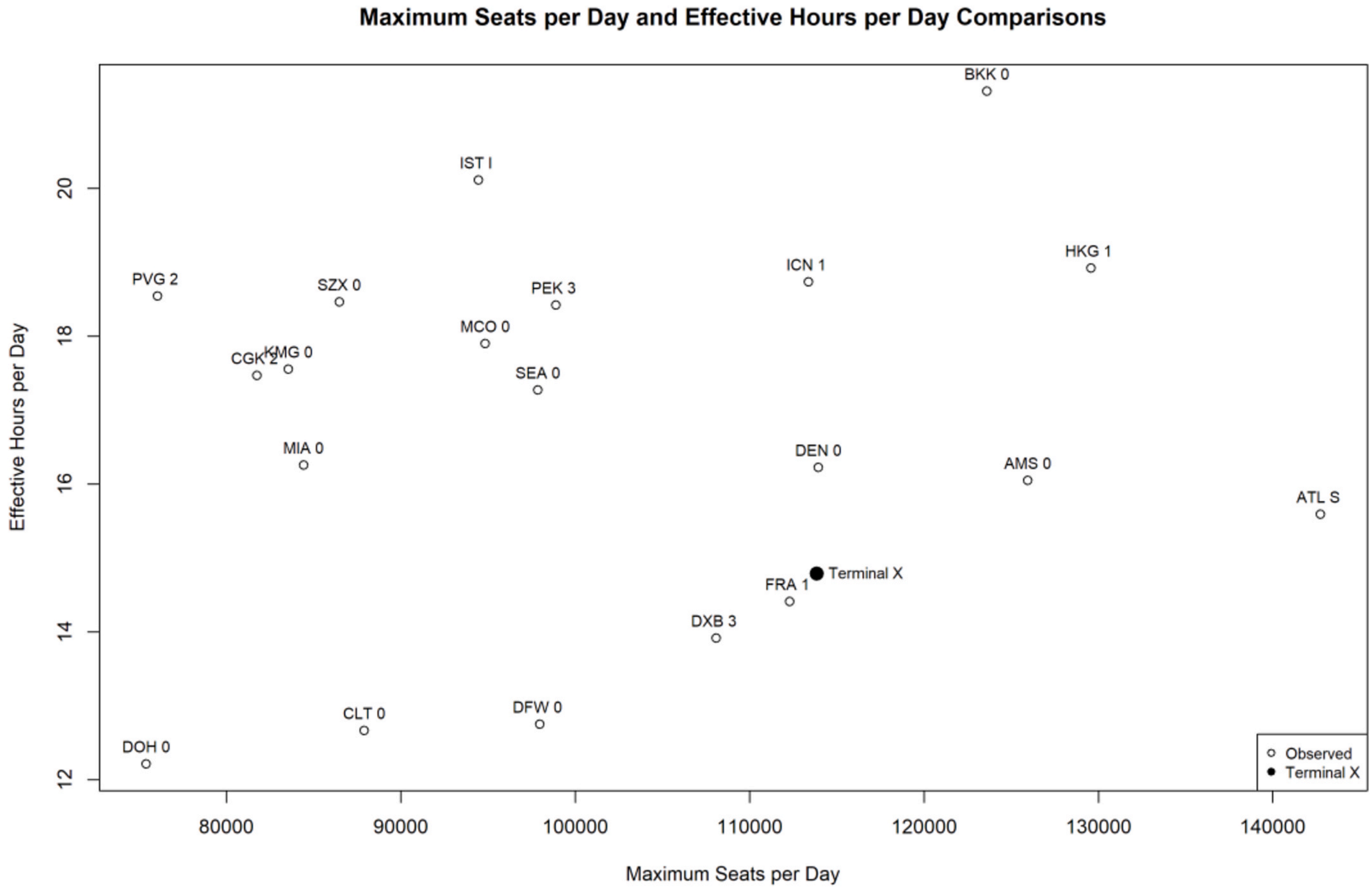


**Fig. 13.** Maximum seats per day and effective hours per day comparisons.

This would require more data to compare scheduled demands and actually observed demands, the latter being affected by systemic and random factors.

## CRediT authorship contribution statement

**John Beasley:** Conceptualization, Methodology, Writing – original draft. **Martin Kunc:** Supervision. **Toni Martinez-Sykora:** Supervision. **Chris N. Potts:** Supervision.

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## Appendix A

### *A. Comparing Standard Busy Rates and Busy Hour Rates*

Two commonly use measures of "peak" demand are the Standard Busy Rate and the Busy Hour Rates:

1. Standard Busy Rate or SBR (which is the same as the 30th Busy Hour taken from road engineering).
2. Busy Hour Rate or BHR (which was adopted by the British Airports Authority and, in that case, was the demand above which 5% of total annual traffic operates beyond the design basis (Matthews, 1995; Reichmuth et al., 2011)).

In this Annex we show the observed relationship between these two measures.

The dataset was processed to calculate SBR and BHR metrics for each combination of airport, terminal, and arrival/departure direction. Plotting BHR against SBR yielded the graphs shown in Figure A.1Error! Reference source not found. The left-hand graph (plotted with linear scales) shows the clear correlation between the two measures.

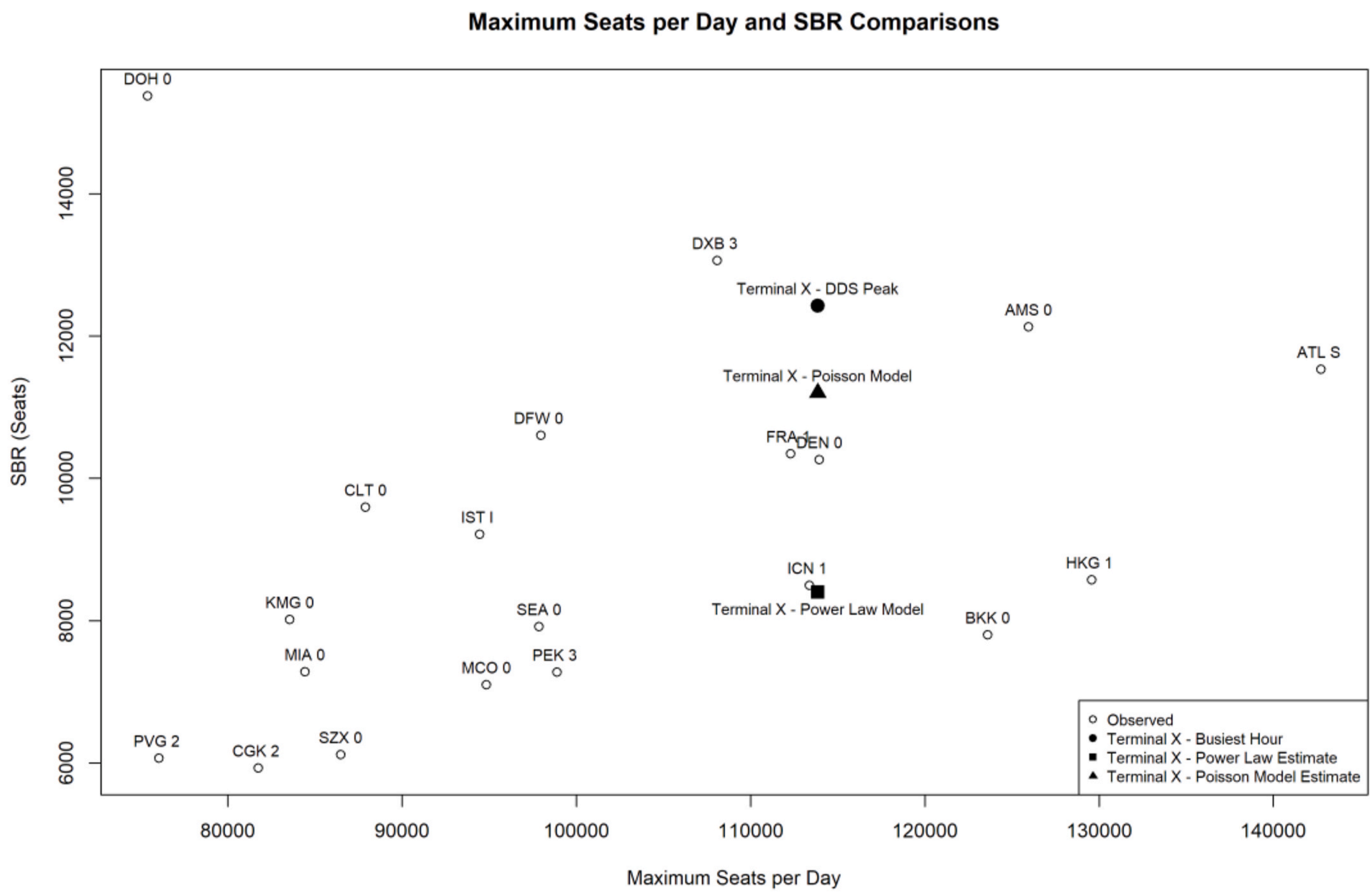


**Fig. 14.** Maximum seats per day and SBR comparisons.

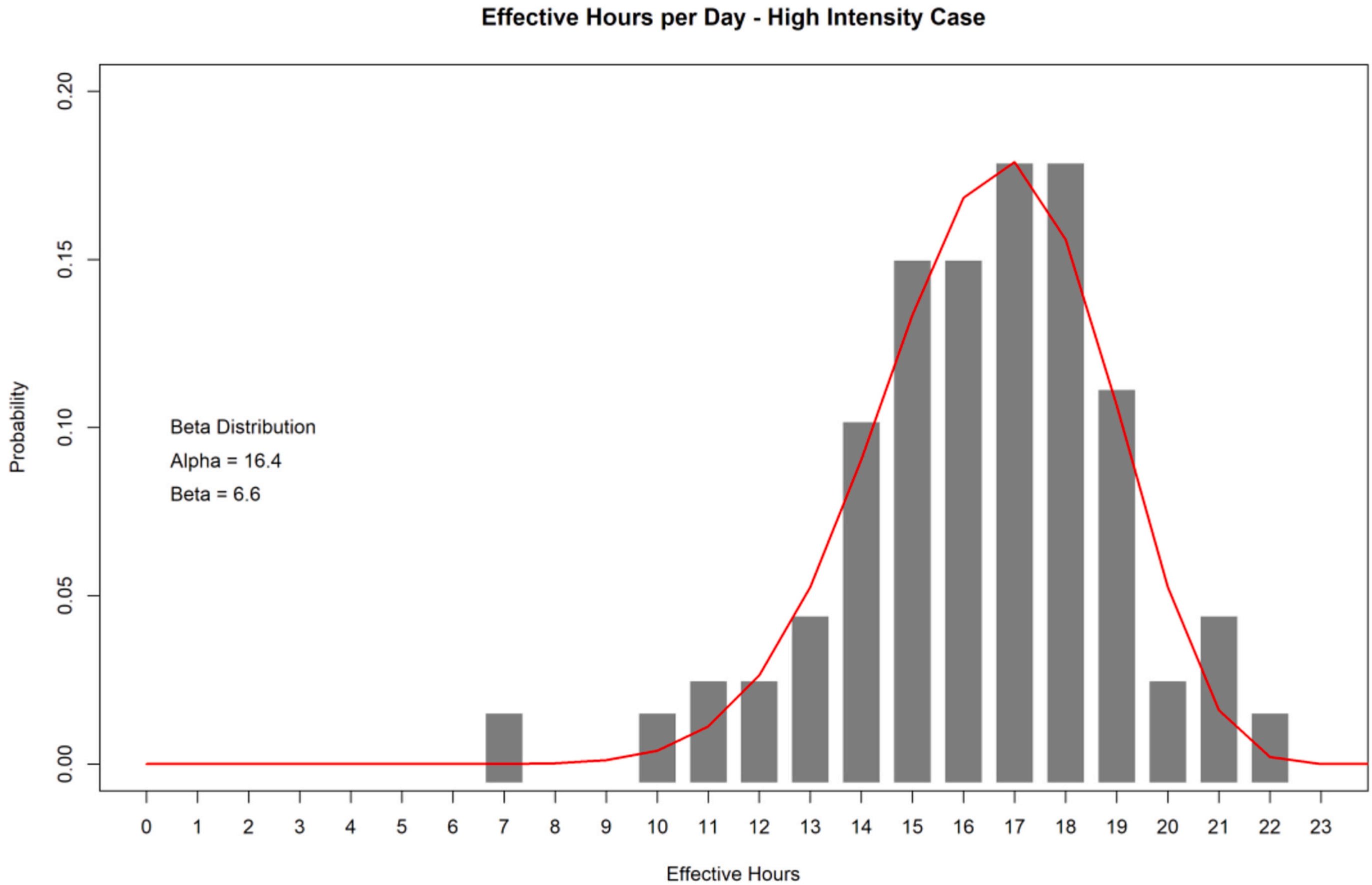


**Fig. 15.** Distribution of effective hours per day (high intensity case).

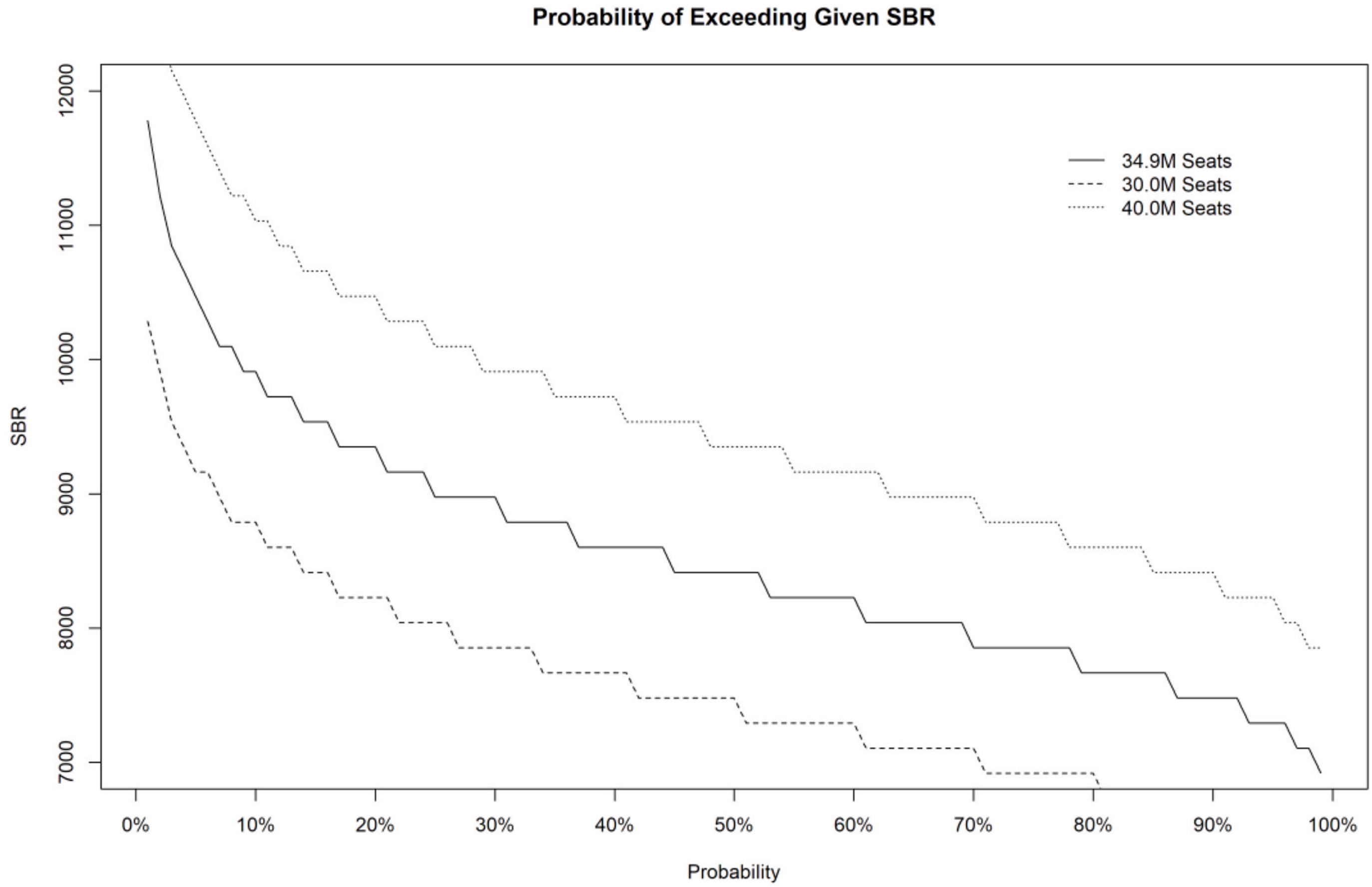


**Fig. 16.** Expected SBR values given distribution of historical effective hour results.

**Table 6**
Example project capital costs.

| Project | Annual pax | Capital cost | Cost/Annual pax |
|---|---|---|---|
| T5 | c. 26 million | £4.3 bn | £165 |
| Incheon | c. 30 million | $6.0 bn | $200 |

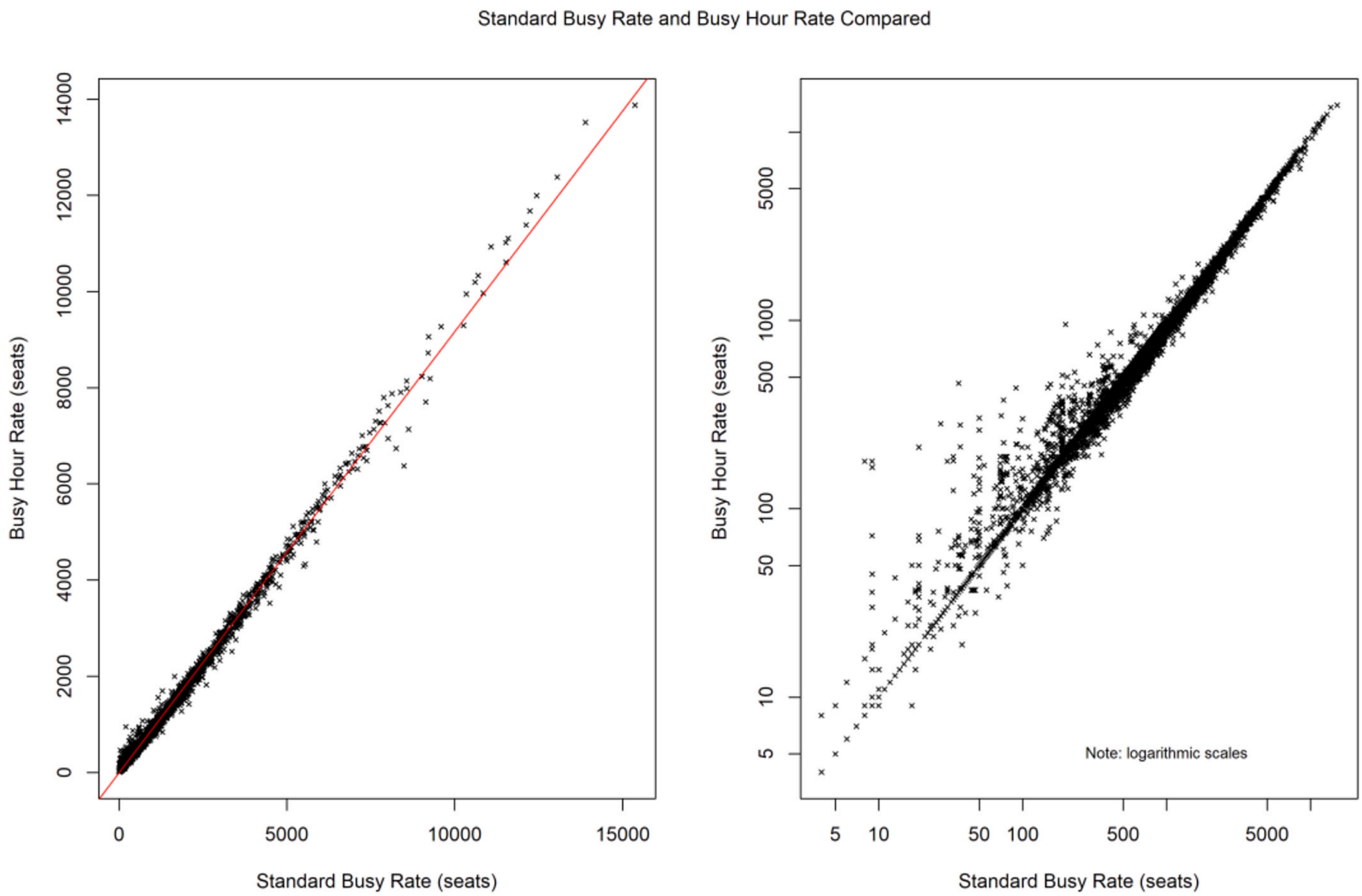


**Fig. A.1.** SBR and BHR Compared

A linear regression model (with the intercept constrained to the origin) was fitted to the observed data (red line). The slope of the resulting line is 0.9166 and the adjusted R-squared value was 0.9964:

$$\text{BHR} = 0.9166 \times \text{SBR}.$$

This indicates that BHR values are, on average, 92% of the equivalent SBR. Other things being equal, using an SBR means that greater capacity will be built into a design compared with using a BHR. The range of SBR values from the dataset covers 4 seats to 15,373 seats in an hour – more than three orders of magnitude. The linear plot is somewhat flattering so a plot of the same data but with logarithmic scales is also included in Figure A.1. This shows a degree of divergence from the simple linear model, particularly for smaller values of SBR and BHR, but the correlation is still clear. We conclude that, while numerically different, the degree of correlation is so high between the two metrics that either could be used as a proxy for short-term demands, though the choice of absolute levels (e.g. 20th or 40th hour, 5% or 2%, say) is what will determine delivered capacity and hence will have a bearing on service quality. For the purposes of this paper, we used the SBR as the chosen metric – it is marginally simpler to calculate than the BHR – but the principles developed apply to both.

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