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Flexible facility requirements for strategic planning of airport passenger terminal infrastructure

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ABSTRACT

Facility requirements determine how and when the capacity of airport passenger terminal facilities is adjusted over time to meet expected demand. Given high levels of uncertainty inherent in long-term airport planning, under and over provision of capacity is a recurrent risk, as conventional strategic planning methods fail to adapt dynamically to changing circumstances. This paper introduces a novel flexible capacity expansion model for airport terminals that considers simultaneously real options 'on' and 'in' systems. The model is validated for the provision of check-in facilities at Zurich Airport. Results confirm suggestions in the literature that incorporating flexibility creates planning and financial advantages over conventional alternatives. Indeed, for the case of Zurich, the financial value of the flexible alternative is approximately 5% higher than the best conventional phased plan. This also suggests that phasing developments can be carefully devised to produce satisfactory outcomes that enable ex-post application of flexibility 'on' systems.

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1. Introduction

An integral part of airport strategic planning (ASP) is the creation and preparation of so-called facility requirements for infrastructures and facilities to be included in the strategic plans. In essence, facility requirements define how and when the capacity of facilities should be adjusted, i.e. expanded or reduced, in future so that the forecast future demand levels can be met in the best possible way (Federal Aviation Authoriy 2015, 2018; International Air Transport Association 2017; International Civil Aviation Organization 1987). The planning process applied to create conventional facility requirements for airport passenger terminal facilities, such as check-in or security control facilities, is, for instance, documented in IATA's *Airport Development Reference Manual* (International Air Transport Association 2017). To determine conventional facility requirements, practitioners require two different inputs: (i) an inventory that describes the current condition and performance of existing facilities, and (ii) a forecast specifying the expected future demand levels of the facility in question (De Neufville et al. 2013). The creation of the inventory is straightforward, as planners only

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need to specify the currently operational infrastructure and its performance (e.g. service times, throughput rates). Regarding demand forecasts for the facility in question, the conventional ASP process recommends to either focus on the future scenario with the highest probability of occurrence, or to specify a range of possible anticipated developments by means of a pessimistic and an optimistic scenario (Sismanidou and Tarradellas 2017; Suh and Ryerson 2019). Given these inputs, practitioners strive for the creation of optimal facility requirements. This refers to facility requirements that avoid the provision of both over-capacity and under-capacity over the entire planning horizon of an ASP project (Dixit and Jakhar 2021). Over-capacity, which describes the provision of too much capacity, is economically not justifiable, as facilities might remain unused over long periods of time and/or even tend to be under-utilised during the peak hours. Neither to be recommended is under-capacity, which refers to the provision of not enough capacity. In such cases, the facility cannot meet its assigned demand volume and is therefore likely to be subject to congestion and delays.

The determination of optimal capacity for airport facilities can be carried on an operational, tactical, or strategic planning level (De Neufville et al. 2013). Operational airport planning deals with a very short planning horizon of some days or weeks (Shuchi, Drogemuller, and Kleinschmidt 2012). For instance, operational planning addresses issues such as staff rostering (Lin, Xin, and Huang 2015; Stolletz 2010), optimal allocation of airport resources for daily operations (Hsu, Chao, and Shih 2012; Ip, Wang, and Cho 2012; Zografos, Madas, and Androutsopoulos 2017), or the optimal management of airport facilities (Kierzkowski and Kisiel 2017; Schultz and Fricke 2011). Tactical planning considers a planning horizon of 2 to 5 years and deals with capacity adjustments within existing facilities, buildings, or airport perimeters (Magalhães, Reis, and Macário 2020). In terms of tactical planning of terminal buildings, for example, De Neufville, de Barros, and Belin (2002) presented a method allowing for the optimal configuration of terminal buildings, while Brunetta, Righi, and Andreatta (1999) introduced a model by which different terminal layouts can be evaluated. For the tactical planning of airport facilities, facility-specific approaches are usually presented. For instance, De Barros and Wirasinghe (2004a) focused on the determination of the optimal number of required shared-use gates, or De Barros and Wirasinghe (2004b) presented a method aiming to optimally size baggage claim areas. Finally, the aim of strategic planning is to determine optimal capacity levels, i.e. optimal facility requirements, for the entire planning horizon under consideration, which can range from 20 to 50 years (International Air Transport Association 2017). The strategic planning task that allows for the determination of optimal facility requirements, which is carried out not only at airports, but also for a wide range of other infrastructures, is an optimisation problem known in the literature as the conventional capacity expansion problem (CEP) (Luss 1982; Martínez-Costa et al. 2014; Van Mieghem 2003).

Models to solve the CEP can be deterministic in nature as they do not consider uncertainty or the 'stochastic nature of the inputs and parameters of the [model's] formulation', yet most conventional CEP models mentioned in the literature are stochastic (Martínez-Costa et al. 2014, 73). In any case, optimal conventional facility requirements determined with CEP models are provided in the form of a single capacity vector that statically describes how and when the capacity of an infrastructure or facility should best be adjusted in the future. If the conditions, specifications, or assumptions under which the conventional CEP model was evaluated change, conventional facility requirements must be completely reformulated. Because ASP is characterised by long planning horizons of around 20 to 50 years, it is subject to considerable degrees of uncertainty in a number of factors, such as demand, technology, demographics, politics, or regulations (Kincaid et al. 2012; Suh and Ryerson 2019). Therefore, the inflexibility of conventional facility requirements is considered a major drawback (Chambers 2007; De Neufville et al. 2013). Consequently, the application of conventional and therefore inflexible facility requirements 'may result in project failure … if the actual demand [or other factors subject to uncertainty are] significantly different from [what was] anticipated' (Hu, Guo, and Poh 2018, 254). For this reason, flexible facility requirements are needed that are both individual for all future scenarios and able to adapt to ever-changing circumstances (Burghouwt and Huys 2003; De Neufville et al. 2013; Kwakkel, Walker, and Marchau 2010; Magalhães, Reis, and Macário 2017).

To introduce flexibilities in the strategic planning of engineering systems,[1] to which airport passenger terminal facilities can certainly be counted, Trigeorgis (1996) suggests the application of real options which '[represent] a right, but not an obligation … to do something under predefined arrangements' at a future point in time (De Neufville 2003, 7). The literature distinguishes between two types of real options: Real options 'on' systems are sources of managerial flexibility, as they provide system owners with the right but not the obligation to buy, sell, expand and contract systems (Chambers 2007; Kincaid et al. 2012), while real options 'in' systems are design features that are intentionally built into engineering systems with the aim of allowing for physical changes of the system itself (Wang and De Neufville 2005). Real options have proven to be valuable, since they enable system owners and decision makers both to capitalise on potential future opportunities as well as to mitigate or avert risks, based on how uncertainty materialises in the future (Cardin 2014; De Neufville 2000). For this reason, the literature suggests that flexible system designs perform between 10% to 30% better financially than inflexible, i.e. conventional, system designs (De Neufville and Scholtes 2011).

Even though conventional CEP models can determine stochastically optimal conventional facility requirements which consider uncertainty to a certain degree, they are only able to consider 'passive management', which makes the implementation of real options impossible (Schachter and Mancarella 2016). Just recently, a number of authors have extended conventional CEP models to flexible CEP models which allow for the generation of stochastically optimal flexible facility requirements that make use of real options (Cardin and Hu 2016). Flexible CEP models have been applied to a number of different engineering systems, such as multi-storey car parks (De Neufville, Scholtes, and Wang 2006), nuclear power plants (Cardin, Zhang, and Nuttall 2017), on-shore liquid natural gas production facilities (Cardin, Ranjbar-Bourani, and De Neufville 2015), emergency medical services infrastructure (Zhang and Cardin 2017), or waste-to-energy systems (Cardin and Hu 2016; Cardin et al. 2017; Hu, Guo, and Poh 2018; Zhao, Haskell, and Cardin 2018). To the authors' best knowledge, however, flexible CEP models have never been applied in the context of ASP in general and of airport passenger terminal facilities, such as check-in facilities, security checkpoints, etc., in particular. Compared to other engineering systems, the design and sizing of airport passenger terminal facilities, which is strongly dictated by International Air Transport Association (2017), has certain particularities that need to be incorporated into a CEP model, irrespective of whether it is a conventional or flexible one. To be emphasised in this context are on the one hand the fact that passenger terminal facilities are to be sized for an uncertain demand level during a design hour in which pronouncedly high but not absolute maximum traffic loads occur (De Neufville et al. 2013; Waltert et al. 2021). On the other hand, airport planners are given comprehensive levels of service guidelines by International Air Transport Association (2017), which describe what constitutes an optimally designed facility and when facilities are considered to be over-designed or under-designed. These level of service guidelines impose both spatial and temporal design constraints as they specify how much queueing space should be made available in a facility and what acceptable waiting times are for passengers during the design hour. In light of this, the objectives of this paper are firstly to demonstrate how flexible CEP models mentioned in the literature can be adapted and adjusted to the requirements of ASP for airport passenger terminal facilities, secondly to apply a flexible CEP model to determine facility requirements for airport passenger terminal facilities, and thirdly to demonstrate the advantages and implications of flexible facility requirements in the context of ASP. Consequently, this paper contributes to knowledge by tailoring, applying, and discussing a real option-based flexible CEP model to determine flexible facility requirements in the context of ASP for airport passenger terminal facilities.

The remainder of this paper is structured as follows: In Section 2, background information on facility requirements and CEP models is provided. Subsequently, a flexible CEP model for the generation of flexible facility requirements for airport passenger terminal facilities is presented in Section 3. Section 4 contains a practical example in which the methods presented in this study are applied to a real-world planning case. Finally, the results and implications of this study are discussed in Section 5, while conclusions are provided in Section 6.

2. Background

This section provides background information on both the way conventional and flexible facility requirements are formulated as well as the structure and functioning of conventional and flexible CEP models.

2.1. Facility requirements for airport passenger terminal facilities

Conventional facility requirements can be viewed as schedules which define when and how the capacity of a facility is to be adjusted over the entire planning horizon of an ASP project. In the literature (Luss 1982; Martínez-Costa et al. 2014; Van Mieghem 2003), conventional facility requirements for a facility[2] are often formally described by means of a capacity vector $\boldsymbol{K} = [K_1, K_2, \dots, K_T]$, whose elements describe the operational capacity in the planning period $t = 0, 1, \dots, T$. In the context of this paper, the capacity of an airport passenger terminal facility is specified by means of the available number of servers, e.g. check-in desks, security check lanes, etc. Moreover, T refers to the planning horizon of an ASP project and $t = 0$ to the initial conditions which all planning activities are based upon.

The definition of flexible facility requirements is a more complex issue. Instead of defining capacity vectors $\boldsymbol{K}$, flexible facility requirements are often formulated on the basis of decision rules $\mathcal{D}$ (Cardin 2014; Cardin and Hu 2016; Cardin et al. 2017). As such, decision rules are 'heuristic-triggering mechanisms' (Cardin et al. 2017, 1) that '[aim] to emulate the decision-making process' of human beings (Cardin, Zhang, and Nuttall 2017, 227).

Accordingly, 'a decision rule can be abstracted as a function …that maps each scenario of uncertainty …to [an individual] capacity sequence' (Cardin and Hu 2016, 3). Consequently, a decision rule is a guideline for practitioners which prescribes exactly how and when the infrastructure of a facility is to be modified should certain factors, such as demand, demographics, technology, etc., change. In the context of ASP, decision rules therefore govern how real options 'in' and 'on' airport passenger terminal facilities should be exercised.

2.2. Capacity expansion problem

Planners aim to define optimal facility requirements for a facility, which are the solution(s) of CEP models. In the case of a conventional CEP model, optimal conventional facility requirements are expressed with a single capacity vector $\boldsymbol{K}^*$, while for flexible CEP models, optimal flexible facility requirements are described with a parameterisation vector $\boldsymbol{\theta}^*$ for decision rule $\mathcal{D}$. In both cases, optimal facility requirements are regarded as the ones that minimise or maximise the value of an index of merit I by means of which an airport passenger terminal facility is evaluated over the entire planning horizon of an ASP project. According to Martínez-Costa et al. (2014), this index of merit I can either be the net present value (NPV), the sum of all discounted profits, or the sum of all discounted costs incurred by a facility over the entire planning horizon.

Conventional CEP models. As mentioned in the introduction, a clear distinction must be made between conventional and flexible CEP models. Most conventional CEP models are based on the seminal paper of Manne (1961). As such, Manne's CEP model 'consider[s] the trade-off between the economies-of-scale savings of large expansion sizes versus the cost of installing capacity before it is needed' to determine when and how the capacity of a certain infrastructure should be adjusted best over time, in order to meet demand (Luss 1982, 908). While Manne (1961) focuses solely on capacity expansions, the literature also mentions conventional CEP models that allow for capacity reductions (Eppen, Martin, and Schrage 1989), capacity replacement, depreciation and degradation (Rajagopalan 1998), infrastructure renewal (Benedito et al. 2016), technology replacement (Wang and Nguyen 2017), outsourcing (Rajasekharan and Peters 2000), or a combination of these. Besides, given the timing and sizing of capacity adjustments, CEP models might also consider a solution optimisation in terms of the type and location of capacity provided (Martínez-Costa et al. 2014; Van Mieghem 2003). Single-facility models consider one type of facility, while multi-facility models account for more than one type. Similarly, single-location models consider only one geographic location, while in multi-location models the facilities are situated at different geographic sites.

The literature presents different types of conventional CEP models that are either deterministic or stochastic in nature. Because ASP is characterised by long planning horizons which makes it susceptible to uncertainty, conventional facility requirements applied in the context of ASP should be determined with stochastic CEP models wherever possible. To this end, a conventional stochastic single-type and single-location CEP model can be described by means of an optimisation problem, which, depending on the chosen index of merit I, resembles either a maximisation or a minimisation problem. For purposes of illustration, Model (1) is formulated as a maximisation problem

$$\max_{\boldsymbol{K}} \quad \mathbb{E}_{\boldsymbol{\xi} \sim \mathcal{F}}\left[I(\boldsymbol{K}, \boldsymbol{\xi})\right] \tag{1a}$$

$$\text{s.t.} \quad K_t \in \mathbb{N}_0, \quad \forall t = 0, \ldots, T \tag{1b}$$

where $\mathbb{E}[\cdot]$ is the expectation, and $\boldsymbol{\xi} = [\xi_1, \xi_2, \ldots, \xi_T]$ is a random vector following a known (multi-dimensional) distribution function $\mathcal{F}$ which describes the evolution of (some of) the above-mentioned uncertain factors ASP is subject to, over all planning periods t considered. Because the capacity of airport passenger terminal facilities is both indivisible and non-negative,[3] Constraint (1b) ensures that the elements K_t of the capacity vector $\boldsymbol{K}$ are non-negative integers.

Stochastic CEP models can be quite challenging to solve in practice. For this reason, a finite number of scenarios of uncertainty $\Omega = \{\boldsymbol{\xi}^1, \boldsymbol{\xi}^2, \ldots, \boldsymbol{\xi}^S\}$ is often created and used instead of a random variable $\boldsymbol{\xi}$ (Dupačová, Consigli, and Wallace 2000). This way, a deterministic counterpart of the conventional CEP model is created (Bakker, Dunke, and Nickel 2020). Similarly to Model (1), a maximisation problem is formulated below for illustrative purposes

$$\max_{\boldsymbol{K}} \quad \sum_{s=1}^{S} p_s I(\boldsymbol{K}, \boldsymbol{\xi}^s) \tag{2a}$$

$$\text{s.t.} \quad K_t \in \mathbb{N}_0, \quad \forall t = 0, \ldots, T \tag{2b}$$

where $0 \leq p_s \leq 1$ is the probability of occurrence of scenario $\boldsymbol{\xi}^s \in \Omega$. It is often assumed that all scenarios have an identical probability of occurrence $p_1 = p_2 = \ldots = p_S$. Moreover, $\sum_{s=1}^{S} p_s = 1$ must be ensured in any case.

Many conventional CEP model-related applications have been presented in the literature (Luss 1982; Martínez-Costa et al. 2014; Van Mieghem 2003). As such, most of these contributions focus on strategic planning applications in the manufacturing, telecommunications, or service industries (Martínez-Costa et al. 2014). Only a few authors have proposed applications of conventional CEP models in the context of ASP. Exemplars include Solak (2007) and Solak, Clarke, and Johnson (2009), who introduce a holistic airport terminal capacity planning model, as well as Sun and Schonfeld (2015, 2016, 2017), who developed a series of capacity planning models for airport facilities in general. Further examples are the facility-specific modelling approaches for the strategic capacity planning of airport gates (Chen and Schonfeld 2013), and for baggage carousels (Yoon and Jeong 2015).

Flexible CEP models. One way in which conventional CEP models can be made flexible is through the integration of decision rules that define how real options 'in' and 'on' a system available to planners should be exercised (Cardin, De Neufville, and Geltner 2015; Cardin and Hu 2016; Cardin et al. 2017; Cardin, Zhang, and Nuttall 2017). A decision rule $\mathcal{D}$ is a function which, for each scenario of uncertainty $\boldsymbol{\xi}^s \in \Omega$, specifies the operational capacity K_t^s to be provided in planning period t, given the state or value of several factors, such as the history or the path of the already disclosed uncertainty $\boldsymbol{\xi}^s_{[t]} = [\xi^s_1, \ldots, \xi^s_t]$ in planning period t, and/or the operational capacity K^s_{t-1} at the beginning of planning period t. Consequently, operational capacity K_t^s in planning period t and for scenario s can be described with decision rule $\mathcal{D}$ as follows

$$K_t^s = \mathcal{D}(\boldsymbol{\xi}_{[t]}^s, K_{t-1}^s, \boldsymbol{\theta}) \tag{3}$$

where $\boldsymbol{\theta}$ is an unknown parameter vector of decision rule $\mathcal{D}$. As such, four different types of decision rules are presented in the literature: (i) constant decision rules (Cardin et al. 2017) make decisions that are independent of the disclosed uncertainty at planning period t, (ii) linear decision rules (Cardin et al. 2017) make decisions in scenario s and planning period t based on a linear function of disclosed uncertainty $\boldsymbol{\xi}_{[t]}^s$, (iii) nonlinear decision rules (Georghiou, Kuhn, and Wiesemann 2019) employ a nonlinear function of the disclosed uncertainty $\boldsymbol{\xi}_{[t]}^s$, while (iv) conditional-go decision rules (Cardin and Hu 2016; Cardin, Ranjbar-Bourani, and De Neufville 2015; Cardin et al. 2017; Cardin, Zhang, and Nuttall 2017; Zhang and Cardin 2017) are based on if-then-else statements executed for every scenario s and planning period t. The integration of a decision rule in a conventional CEP model leads to the following definition of a flexible CEP model, which in this case is also exemplarily formulated as a maximisation problem

$$\max_{\boldsymbol{\theta}} \quad \sum_{s=1}^{S} p_s I(\boldsymbol{K}^s, \boldsymbol{\xi}^s, \boldsymbol{\theta}) \tag{4a}$$

$$\text{s.t.} \quad K_t^s \in \mathbb{N}_0, \quad \forall t = 0, \ldots, T, \forall s = 1, \ldots, S \tag{4b}$$

$$K_t^s = \mathcal{D}(\boldsymbol{\xi}_{[t]}^s, K_{t-1}^s, \boldsymbol{\theta}), \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, S \tag{4c}$$

$$K_0^s = K_0, \quad \forall s = 1, \ldots, S \tag{4d}$$

3. Methods

This section presents the methods required to create flexible facility requirements for airport passenger terminal facilities in the context of ASP. To this end, Section 3.1 defines the index of merit used to evaluate facility requirements, Section 3.2 sets out the ASP-specific CEP models, Section 3.3 describes the solution procedure applied to solve the proposed CEP models, and Section 3.4 explains how the proposed CEP models are applied to a real world case.

3.1. Index of merit

To determine optimal facility requirements, feasible solution candidates, i.e. facility requirements that are theoretically possible, are evaluated by means of a certain index of merit. In this study, an index of merit based on the concept of the NPV is applied to evaluate facility requirements. In theory, the NPV is defined as the discounted sum of all costs incurred and revenues generated by a facility or project over the entire planning horizon. However, in the context of ASP, the inclusion of revenues and costs covering the entire planning horizon is not desirable, since, according to standard industry practice (De Neufville et al. 2013; International Air Transport Association 2017), an airport passenger terminal facility is exclusively designed for the traffic volume during the design hour d_t, which is the so-called design hour load (Waltert et al. 2021). For this reason, the index of merit I proposed in this study is based on the discounted sum of all costs incurred and revenues generated exclusively during the design hours of every planning period $t = 1, 2, \ldots, T$ considered in an ASP project. For an airport passenger terminal facility, the index of merit I can therefore be formulated as

$$I = -\mathcal{C}_0 + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} (\mathcal{R}_t - \mathcal{C}_t) \tag{5}$$

where $\mathcal{C}_0$ are initial costs incurred at time $t=0$, $\mathcal{R}_t$ and $\mathcal{C}_t$ are revenues generated and costs incurred by the airport passenger terminal facility during the design hour of planning period t, and δ is the discount factor. In the following, it is explained how the cost and revenue functions are designed to meet the needs of ASP for airport passenger terminal facilities.

Cost function $\mathcal{C}_t$. Following Sun and Schonfeld (2015, 2016, 2017), three different cost components are considered in cost function $\mathcal{C}_t$, namely installation costs CI_t, operational costs CO_t, and capacity mismatch costs[4] CM_t.

$$\mathcal{C}_t = CI_t + CO_t + CM_t \tag{6}$$

Installation costs CI_t are incurred when the capacity of the facility is expanded by ΔK_t units of capacity, and, in the course of this, the building space required by the facility must be adjusted by ΔA_t units of building space. The additional building space ΔA_t required to accommodate capacity expansion ΔK_t is estimated with an analytical model[5] presented in International Air Transport Association (2017), which is defined as

$$\Delta A_t = \underbrace{(1+p_{circ})}_{\text{space for circulation}} \cdot \left(\underbrace{\Delta K_t \cdot A_K}_{\text{space for servers}} + \underbrace{Q_t^{\max} \cdot A_Q}_{\text{space for queue}} \right) \tag{7}$$

where p_{circ} is the percentage of the total building space allocated for circulation space for passengers, e.g. corridors, hallways, stairs, etc., A_K is the required building space per unit of capacity of the facility, e.g. the space for a single check-in desk, $Q_t^{\max}$ is the expected maximum number of passengers in the queue of the facility during the design hour of planning period t, and A_Q is the level of service (LoS) space standard, which specifies the building area allotted to each passenger waiting in the queue in front of the facility. While p_{circ}, A_K, and A_Q are specified on the basis of historical observations, local preferences, and/or experience values of airport operators, $Q_t^{\max}$ can be approximated with the following formula mentioned in International Air Transport Association (2017)

$$Q_t^{\max} = QF\,(MQT) \cdot d_t \cdot PK \tag{8}$$

where $QF(MQT)$ is a function determining a correction factor, d_t is the design hour load of the facility in planning period t, and PK is the peak 30-minute factor, which expresses the percentage of passengers that are handled within the 30 busiest minutes of the design hour. The correction factor QF depends on the selected value of the maximum queueing time MQT, which is the temporal target LoS standard that specifies the maximum acceptable waiting time a passenger experiences in the facility during the design hour.[6]

The installation costs resulting from a capacity expansion of $\Delta K_t \geq 0$ units of capacity and $\Delta A_t \geq 0$ units of building space is estimated by means of Equation (9), which is based on the concept of power cost functions, as for instance described in Luss (1982):

$$CI_t = \frac{(1 + p_{ohd}) \cdot (ci_K \cdot (\Delta K_t)^\alpha + ci_A \cdot (\Delta A_t)^\alpha)}{h_t} \tag{9}$$

where ci_K and ci_A are unit installation costs for capacity and building space expansions, $0 \leq \alpha \leq 1$ is the economies of scale factor, h_t is the total number of operating hours[7] in planning period t, and p_{ohd} is a factor describing the overhead costs of an infrastructure expansion project.

Operational costs CO_t specify the costs of operation of the facility during the design hour of planning period t. In this study, operational costs are approximated with the following linear function

$$CO_t = K_t \cdot co_K + A_t \cdot co_A \tag{10}$$

where co_K, and co_A are unit operating costs per unit of capacity and building space, respectively.

Based on the works of Saffarzadeh and Braaksma (2000), capacity mismatch costs CM_t are incurred if capacity K_t operational in planning period t is either considered over-designed or under-designed. An over-designed facility is characterised by the fact that too much infrastructure is available during the design hour, which potentially leads to under-utilisation and subsequently to average passenger waiting times that are significantly below the temporal target LoS standard MQT. Contrary, in an under-designed facility too little infrastructure is provided, which results in average waiting time experienced by passengers during the design hour that are significantly larger than MQT. Both the over-design and the under-design of airport passenger terminal facilities should be avoided. To account for the undesirability of these conditions, it is assumed that capacity mismatch costs CM_t arise in both cases.

To determine capacity mismatch costs CM_t, a range of acceptable values for the temporal target LoS standard MQT, specified by parameters $MQT^{\min}$ and $MQT^{\max}$, must be defined first. For this purpose, International Air Transport Association (2017) published recommendations on acceptable temporal target LoS values for a number of different airport passenger facility types. Alternatively, parameters $MQT^{\min}$ and $MQT^{\max}$ can also be specified by airport planners on a case-by-case basis to reflect local needs and peculiarities. In a second step, $MQT^{\min}$ and $MQT^{\max}$ are translated into capacity threshold levels K_t^O and K_t^U, which, given a certain design hour load d_t, specify the range of capacity required in the facility so that the temporal target LoS specifications can be met. To determine capacity threshold levels K_t^O and K_t^U, the following rule-of-thumb capacity model provided by International Air Transport Association (2017) is applied

$$K_t^O = \frac{d_t \cdot PK \cdot \frac{PK}{60}}{30 + MQT^{\min}} \quad K_t^U = \frac{d_t \cdot PK \cdot \frac{PK}{60}}{30 + MQT^{\max}} \tag{11}$$

where PK is the peak 30-minute factor of the facility and PT is the observed average processing time[8] per passenger in the facility. In a final step, capacity mismatch costs CM_t are calculated as follows

$$CM_t = \begin{cases} 0 & \text{if } K_t^U \leq K_t \leq K_t^O \quad \text{(optimal capacity)} \\ \left(K_t - K_t^O\right)^{\alpha_M} \cdot cm^O, & \text{if } K_t \geq K_t^O \quad \text{(over-design)} \\ \left(K_t^U - K_t\right)^{\alpha_M} \cdot cm^U, & \text{if } K_t < K_t^U \quad \text{(under-design)} \end{cases} \tag{12}$$

where cm^O are unit capacity mismatch costs of over-design, cm^U are unit capacity mismatch costs of under-design, and α_M is a coefficient used to express the nonlinearity of capacity mismatch-related costs, as proposed by Sun (2016) and Sun and Schonfeld (2015, 2016, 2017).

Revenue function $\mathcal{R}_t$. In accordance with Ju, Wang, and Che (2007), the revenues generated by the facility during the design hour in planning period t is approximated with the following function

$$\mathcal{R}_t = \begin{cases} d_t \cdot r_d + \left\lceil \frac{d_t}{\mu_K} \right\rceil \cdot r_K & \text{if } K_t > \left\lceil \frac{d_t}{\mu_K} \right\rceil \\ d_t \cdot r_d + K_t \cdot r_K & \text{if } K_t \leq \left\lceil \frac{d_t}{\mu_K} \right\rceil \end{cases} \tag{13}$$

where r_d refers to the unit revenue per design hour passenger, r_K to the unit revenue per unit of capacity K_t, $\lceil \cdot \rceil$ is the ceil function, and μ_K is the unit throughput rate of one single server of the passenger terminal facility during the design hour. With regard to revenues r_K generated per unit of capacity of the facility, it is assumed that airport operators may charge fees for the provision of facilities to airlines and/or handling agents, e.g. user fee per check-in desk and unit of time. For passenger-related revenues r_d, an average revenue per passenger and facility is assumed.

3.2. CEP models

Optimal conventional and optimal flexible facility requirements for airport passenger terminal facilities are determined with the help of a conventional CEP model and a flexible CEP model, respectively. These CEP models are developed based on the assumption that an ASP project is influenced exclusively by uncertainty of passenger demand. Consequently, a conventional CEP model for ASP applications can be derived by combining the model stipulated in Equation (2) and index of merit specified in Equation (5):

$$\max_{\boldsymbol{K}} \quad \sum_{s=1}^{S} p_s \left[-\mathcal{C}_0(\Delta K_0) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_t(d_t^s, K_t) - \mathcal{C}_t(d_t^s, K_t) \right) \right] \tag{14a}$$

$$\text{s.t.} \quad K_t \in \mathbb{N}_0, \quad \forall t = 0, \ldots, T \tag{14b}$$

$$\Delta K_t = K_t - K_{t-1}, \quad \forall t = 1, \ldots, T \tag{14c}$$

$$\Delta K_0 \in \mathbb{N}_0 \tag{14d}$$

$$0 \leq \Delta K_t \leq \Delta K^{\max}, \quad \Delta K^{\max} \in \mathbb{N}_0, \forall t = 0, \ldots, T \tag{14e}$$

where $\boldsymbol{D}^s = [D_1^s, D_2^s, \ldots, D_T^s]$ are annual aggregated passenger demand scenarios for an airport expressed in PAX per year, $f(D_t^s)$ is a function which converts every annual aggregated demand scenario $\boldsymbol{D}^s$ into a design hour load scenario $\boldsymbol{d}^s = [d_1^s, d_2^s, \ldots, d_T^s]$ for an airport passenger terminal facility, and $\Delta K^{\max} \in \mathbb{N}_0$ defines the maximum capacity adjustment size. Annual aggregated demand scenarios $\boldsymbol{D}^s$ are generated with a standard geometric Brownian motion (GBM) process (Cardin 2014; Cardin and Hu 2016; Hu, Guo, and Poh 2018). In the context of this study, this GBM process can be used to determine the change of annual aggregated demand $\Delta D_t = D_{t+1} - D_t$ in planning period t as follows

$$\frac{\Delta D_t}{D_t} = \mu_D \Delta t + \sigma_D \Delta W_t \tag{15}$$

where ΔW_t refers to independent and identically distributed (i.i.d.) increments of the Wiener process, while parameters μ_D and σ_D specify the percentage drift rate and the percentage of volatility of annual aggregated passenger demand, respectively. These parameters, which are unknown, can be determined from a sample of historical aggregated passenger demand observations. De Weck, Eckert, and Clarkson (2007) suggest estimating μ_D by means of the sample mean and σ_D with the sample standard deviation. Subsequently, annual aggregated demand scenarios $\boldsymbol{D}^s$ are converted into airport passenger terminal facility-specific design hour load scenarios $\boldsymbol{d}^s$ with a linear regression model documented in Waltert et al. (2021).

The flexible CEP model applied in this study is derived by combining the model defined in Equation (4a) with index of merit specified in Equation (5)

$$\max_{\boldsymbol{\theta}} \quad \sum_{s=1}^{S} p_s \left[-\mathcal{C}_0(\Delta K_0^s) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_t(d_t^s, K_t^s) - \mathcal{C}_t(d_t^s, K_t^s) \right) \right] \tag{16a}$$

$$\text{s.t.} \quad K_t^s \in \mathbb{N}_0, \quad \forall t = 0, \ldots, T, \forall s = 1, \ldots, S \tag{16b}$$

$$K_t^s = \mathcal{D}(\boldsymbol{d}_{[t]}^s, K_{t-1}^s, \boldsymbol{\theta}), \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, S \tag{16c}$$

$$\Delta K_t^s = K_t^s - K_{t-1}^s, \quad \forall t = 1, \ldots, T, \forall s = 1, \ldots, S \tag{16d}$$

$$\Delta K_0^s \in \mathbb{N}_0, \quad \forall s = 1, \ldots, S \tag{16e}$$

$$0 \le \Delta K_t^s \le \Delta K^{\max}, \quad \Delta K^{\max} \in \mathbb{N}_0, \forall t = 0, \ldots, T, \forall s = 1, \ldots, S \tag{16f}$$

$$K_0^s = K_0, \quad K_0 \in \mathbb{N}_0, \forall s = 1, \ldots, S \tag{16g}$$

$$\boldsymbol{\theta} = [\theta_1, \theta_2], \quad \theta_1, \theta_2 \in \{0, 1, \ldots, \Delta K^{\max}\}, \quad \Delta K^{\max} \in \mathbb{N}_0 \tag{16h}$$

where Constraint (16c) specifies the decision rule that governs how real options 'in' and/or 'on' a facility are exercised. The literature mentions several different types of decision rules which can be applied for the determination of flexible facility requirements of engineering systems, namely constant, linear, nonlinear, and conditional-go decision rules (Cardin, De Neufville, and Geltner 2015; Cardin and Hu 2016; Cardin et al. 2017; Cardin, Zhang, and Nuttall 2017; Zhang and Cardin 2017). In this study, a conditional-go decision rule, is used. This decision rule depends on three different inputs: the history of the already disclosed design hour load demand $\boldsymbol{d}_{[t]}^s$ at planning period t and scenario s, the installed capacity K_{t-1}^s at the beginning of planning period t and scenario s, and a parameterisation vector $\boldsymbol{\theta} = [\theta_1, \theta_2]$. The functionality of a conditional-go decision rule can be abstracted using an if-then-else statement. The if-statement checks whether the difference between the observed design hour load demand d_t^s and the facility's throughput that can be realised given the operational capacity K_{t-1}^s available at the beginning of planning period t and scenario s is smaller than $\theta_2 \cdot \mu_K$

$$d_t^s - K_{t-1}^s \cdot \mu_K > \theta_2 \cdot \mu_K \quad (17)$$

where μ_K is the unit throughput rate of one single server of the passenger terminal facility, and θ_2 is a parameter of the decision rule. Should the if-statement be true, then the capacity of the facility is adjusted in planning period t and scenario s to

$$K_t^s = K_{t-1}^s + \theta_1 \quad (18)$$

where θ_1 is a parameter of the decision rule. Otherwise, the actions specified in the else-part of the rule are applied, which, in the case of this study, state that the capacity remains unchanged at $K_t^s = K_{t-1}^s$.

3.3. Solution procedure

The decision variable of the proposed conventional CEP model is capacity vector $\boldsymbol{K}$, while parameterisation vector $\boldsymbol{\theta}$ is the decision variable of the flexible CEP model. As defined in Constraints (14b), (16b), and (16h), $\boldsymbol{K}$ and $\boldsymbol{\theta}$ are integers. Subsequently, the size of the resulting solution spaces of both the conventional and the flexible CEP model proposed in this study depend significantly on the chosen values for parameters T and $\Delta K^{\max}$, which ultimately define the theoretically possible number of permutations of capacity vector $\boldsymbol{K}$ and parameter vector $\boldsymbol{\theta}$. As long as reasonably[9] small values for these parameters are chosen, both CEP models proposed in this study can be solved with the enumeration technique. In this process, all possible solution candidates are evaluated one after the other for their quality, and finally the solution candidate that leads to the highest value of the selected index of merit is chosen as the optimal solution, i.e. the optimal conventional facility requirements and the optimal flexible facility requirements. If planners need to choose larger values for parameters T and $\Delta K^{\max}$, more advanced solution procedures, such as a genetic optimisation algorithm, could be applied. In the context of strategic airport passenger terminal planning, however, realistic values for parameters T and $\Delta K^{\max}$ are somewhat limited. On the one hand, the choice of very long planning horizons T for planning at the level of detail presented in this paper makes little sense. On the other hand, the maximum expansion size $\Delta K^{\max}$ is constrained in most airport passenger terminals due to space restrictions. Consequently, the application of the enumeration technique in this paper is justified.

3.4. Application of the CEP models

The conventional and flexible CEP models for airport passenger terminal facilities developed in this paper are applied to a practical case centred on the determination of facility requirements for all check-in infrastructures used at Zurich Airport (ZRH) by home carrier Swiss International Airlines and its partners. These check-in infrastructures are situated in different locations within ZRH Airport's Terminals 1 and 3. Hence, to simplify the case, it is assumed that all check-in infrastructures are co-located in one single area, referred as Check-in 1 and 3 from now on, and for which facility requirements are generated.

4. Results

In this section, the results of the application of the models to ZRH Airport's Check-in 1 and 3 facilities are presented. In this context, demand scenarios, for both annual aggregated passenger demand for ZRH Airport and design hour load demand for Check-in 1 and 3 are presented in Section 4.1. Subsequently, Section 4.2 presents optimal conventional and optimal flexible facility requirements for the facilities, while Section 4.3 analyses the results in terms of their financial value.

4.1. Demand scenarios

Based on a sample of historical observations for annual aggregated passenger demand at ZRH Airport covering the years 2009 to 2019, as reported in Flughafen Zürich AG (2021), the percentage drift rate of aggregated demand and the percentage volatility are estimated at $\hat{\mu}_D = 3.723\%$ and $\hat{\sigma}_D = 2.699\%$, respectively. Subsequently, based on the observed demand D_0 in the year 2019, a set of 5000 independent annual aggregated demand scenarios was created using the GBM model, see Equation (15). In the upper diagram in Figure 1, a randomly selected subset of these annual aggregated demand scenarios $\boldsymbol{D}^s$ for ZRH Airport is depicted for illustrative purposes.

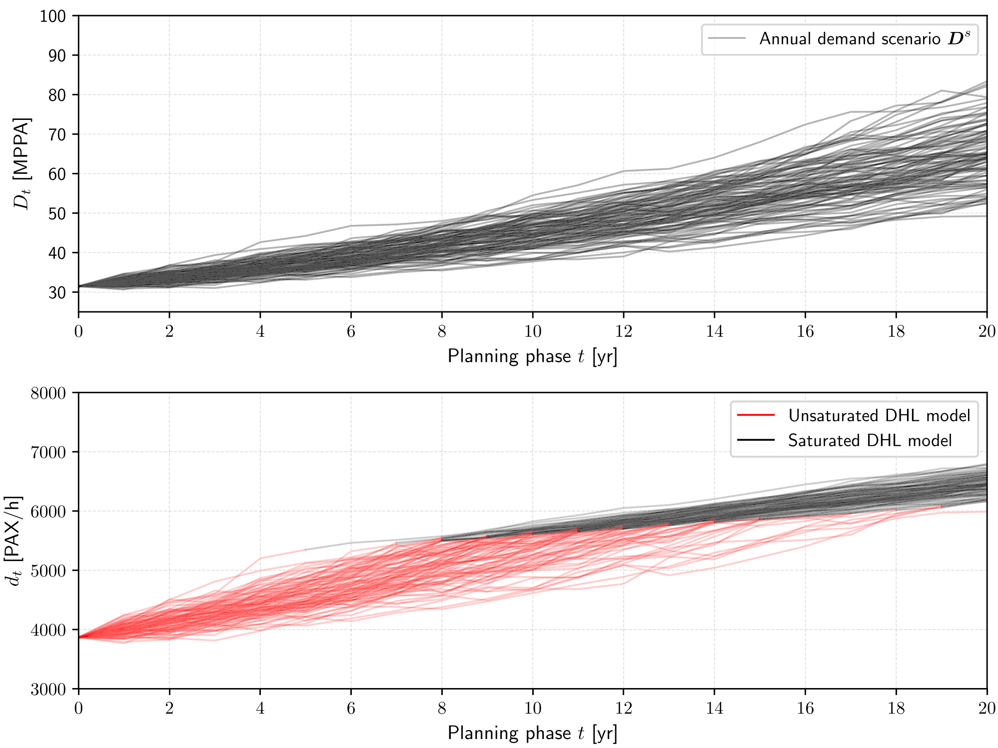

Figure 1. 100 randomly selected annual aggregated demand scenarios for ZRH Airport presented in the unit million passengers per annum (MPPA) (top) and 100 randomly selected design hour load demand scenarios for Check-in 1 and 3 at ZRH Airport (bottom).

The annual aggregated demand scenarios were converted into design hour load demand scenarios for Check-in 1 and 3 by means of the ratio-based design hour load model derived by Waltert et al. (2021). The work of Waltert et al. (2021) focuses on the security control facilities at ZRH Airport, which are located upstream of Check-in 1 and 3, thus, the parameterisation of the design hour load model documented in Waltert et al. (2021) is applicable in this case too. The diagram displayed at the bottom of Figure 1 illustrates 100 randomly selected design hour load scenarios $\boldsymbol{d}^s$ for Check-in 1 and 3 over the selected planning horizon. In the diagram, each design hour load scenario is divided into an unsaturated and a saturated segment. While in the unsaturated segment design hour load demand d_t^s is only dependent on aggregated demand D_t, the capacity of the runway system is used to constrain growth of d_t^s in the saturated segment.

4.2. Optimal facility requirements for check-in 1 and 3

In this section, optimal conventional facility requirements for Check-in 1 and 3 are compared with flexible requirements for the same facility. To enable a sound comparison, three different variants of the conventional CEP model specified in Equation (14a) were created and subsequently evaluated. These model variants are referred to below as *Fixed A*, *Fixed B*, and *Fixed C*. In the *Fixed A* model variant, it is assumed that the capacity of Check-in 1 and 3 can be adjusted exclusively by an amount ΔK_0 at planning period $t = 0$. Similarly, model *Fixed B* allows only for a single capacity adjustment ΔK_t, which, however, can be made at any planning period $t = 1, 2, \ldots, T$. Model *Fixed C* is characterised by two capacity adjustments ΔK_{t_1} and ΔK_{t_2}, which can be executed at times $t_1, t_2 = 1, 2, \ldots, T, t_1 \neq t_2$. While conventional facility requirements are identically applicable to all scenarios, flexible facility requirements based on a conditional-go decision rule are individual for each scenario. For flexible facility requirements determined by means of the flexible CEP model mentioned in Equation (16a), it is therefore assumed that airport planners can expand the facility by capacity ΔK and an associated building space ΔA both at any planning period t and individually for each scenario s. To this end, we assume that building space required for these expansions is reserved and readily available over the entire planning horizon, which in practice could be realised, for example, through the usage of buffer spaces (Butters 2010) in a passenger building. To showcase how the value of an airport passenger terminal facility can be positively affected only by applying a flexible rather than a conventional strategic plan, this study assumes that (i) costs associated with both ΔK and ΔA are identical for the conventional and flexible models, and (ii) no costs are incurred for the reservation and provision of the buffer spaces.

The conventional and flexible CEP models were solved with the enumeration technique by using parameters $K^{\max} = 50$ and $T = 20$ as constraints. The parameterisation of the cost and revenue functions used in the CEP models is documented in Appendix. The average computing time required to solve the models on a MacBook Pro (14″, 2021) with an M1 Pro processor with 10 CPU-cores are reported in Table 1.[10]

The resulting optimal conventional and flexible facility requirements are depicted in Figure 2 in the form of capacity deployment sequences that illustrate how capacity of Check-in 1 and 3 is changed best over the entire planning horizon. The capacity deployment sequence resulting from conventional facility requirements are identical for all demand scenarios considered. For this reason, they are presented with line plots in Figure 2. In contrast,

Table 1. Optimal facility requirements for Check-in 1 and 3 at ZRH Airport over a planning horizon of 20 years and required solution times to solve the proposed CEP models.

CEP Model	Optimal facility requirements for Check-in 1 and 3	Number of capacity adjustments	Solution time [seconds]
Fixed A	$\Delta K_0^* = 22$ check-in desks	1	0.4
Fixed B	$\Delta K_{t_1}^* = 26$ check-in desks, $t_1 = 3$ years	1	8.8
Fixed C	$\Delta K_{t_1}^* = 15$ check-in desks, $t_1 = 1$ year $\Delta K_{t_2}^* = 15$ check-in desks, $t_1 = 8$ years	2	199.3
Flexible	$\theta_1^* = 4$ check-in desks, $\theta_2^* = 0$ check-in desks	Mean: 8.16, SD: 0.75	22.5

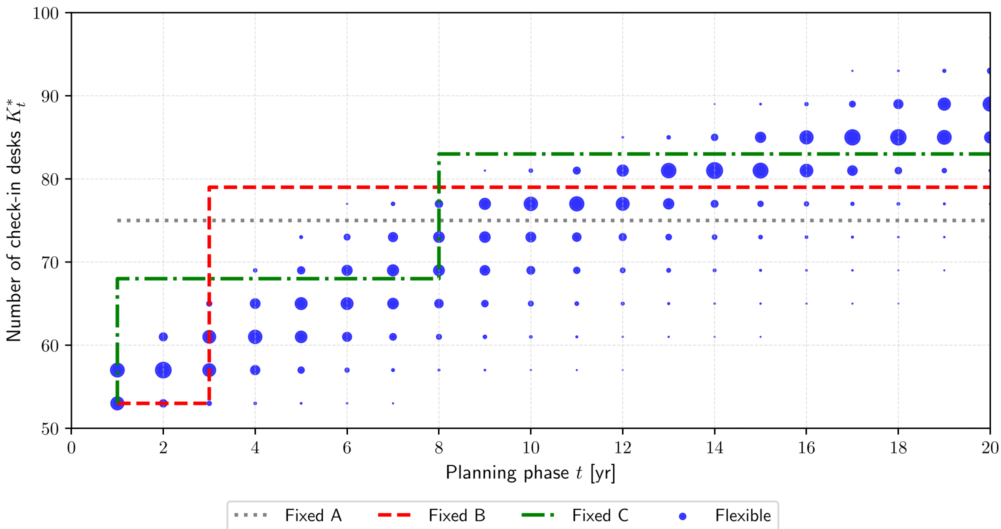

Figure 2. Optimal capacity deployment sequence for Check-in 1 and 3 at ZRH Airport over a planning horizon of 20 years. According to information provided by Flughafen Zürich AG, the initially available capacity in Check-in 1 and 3 is $K_0 = 53$ check-in desks.

capacity deployment sequences resulting from flexible facility requirements are individual for each demand scenario. The blue circles in Figure 2 show qualitatively the probability for the installation of a certain capacity K_t in planning period t. As such, the larger the diameter of a blue circle, the greater the probability that the capacity will take this value. Finally, Table 1 summarises the optimal facility requirements for Check-in 1 and 3 determined with all CEP models.

4.3. Target curves of optimal facility requirements

So-called target curves, which are cumulative probability distributions for the index of merit (NPV in this case), are often used in the literature to compare stochastically optimal facility requirements with each other. Based on the evaluation of the facility requirements over all scenarios considered, target curves '[show] the probability that realised performance will be lower than any specified level or target' (De Neufville and Scholtes 2011, 136). In principle, target curves therefore allow for a quick visual evaluation of different investments incorporating uncertainty about demand and, as in this case, flexibility. Ideally, a curve that is consistently more to the right of another shows an alternative that delivers better returns across various scenarios. If the curves do not cross, then the option that is more to the right is said to be stochastically dominant and it is objectively better than the dominated ones as the resulting index of merit is always higher, irrespective of demand.

Figure 3 depicts the resulting target curves of the conventional facility requirements based on the models *Fixed A*, *Fixed B*, and *Fixed C*, as well as the flexible facility requirements for Check-in 1 and 3. The expected value of the index of merit over all scenarios is shown as vertical lines. The 10% cumulative probability and the 90% cumulative probability, which are referred to in the literature as the value at risk (VaR) and the value at gain (VaG) (De Neufville and Scholtes 2011; Geltner and De Neufville 2018), can be read from the intersection points of the dotted lines with the target curves. VaG indicates how good a particular alternative captures value when market conditions, i.e. demand, are much better than expected. Whereas VaR indicates the degree to which an alternative allows the project owners to shield from losses when demand is substantially lower than expected. Moreover, Table 2 summarises the numerical results provided in Swiss Francs (CHF). To this end, the resulting expectancy of the index of merit, the VaG, the VaR, as well as the observed

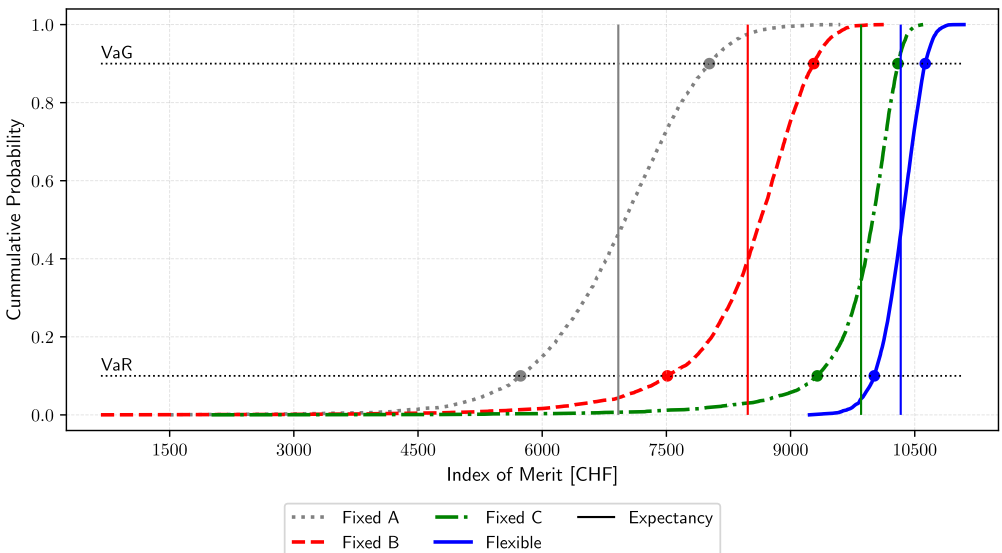

Figure 3. Target curves for optimal fixed and optimal flexible facility requirements for Check-in 1 and 3 at ZRH Airport over a planning horizon of 20 years considering uncertainty in the design hour load.

Table 2. Financial value (NPV) of optimal conventional and flexible facility requirements for Check-in 1 and 3 at ZRH Airport.

CEP Model	$\mathbb{E}[I]$	VaR	VaG	I^{max}	I^{min}
Fixed A	6919.3	5739.3	8018.0	9600.2	1504.2
Fixed B	8482.8	7512.1	9278.7	10125.6	669.7
Fixed C	9851.7	9322.8	10296.9	10601.4	2006.1
Flexible	**10330.6**	**10011.2**	**10626.7**	**11094.3**	**9229.2**

Note: All values referring to the index of merit are provided in Swiss Francs (CHF).

maximum and minimum values are given. Finally, the best performing facility requirement is highlighted in bold type.

5. Discussion

This paper illustrates that conventional and flexible CEP models presented in the literature can be well adapted for an application in the context of ASP for airport passenger terminal facilities. Indeed, the basic idea of a CEP model, namely the search for facility requirements that either maximise or minimise a chosen index of merit, can be adopted one-to-one to the domain of airport planning. Only when defining the index of merit I by means of which facility requirements are evaluated, certain ASP-related peculiarities and planning specifications must be considered. On the one hand, this paper uses an index of merit based on the concept of the NPV which considers exclusively the design hours of all planning periods of an ASP project. This adjustment of the standard NPV is particularly necessary as the capacity of airport passenger terminal facilities must be determined on the basis of the design hour load (Waltert et al. 2021). On the other hand, capacity mismatch costs CM_t which are incurred in both over-designed as well as under-designed facilities, are incorporated in the index of merit. At first glance, these costs seem arbitrary, and it could be argued that capacity mismatch costs should not be included in the index of merit I applied to evaluate facility requirements, as they do not describe the actual financial value of the facility. However, it can be shown that the absolute values of the unit costs of an over-designed facility cm^O and the unit costs of an under-designed facility cm^U have no influence on the determination of optimal facility requirements as long as the ratio cm^O/cm^U remains constant (Saffarzadeh and Braaksma 2000). In fact, capacity mismatch costs represent a valuable tool for practitioners for two reasons. Firstly, planners are given the opportunity to quantify the severity and undesirability of the provision of over-designed or under-designed capacity by selecting appropriate values for cm^O and cm^U. Secondly, any preferences between an over-design and an under-design can be defined. For example, selecting $cm^O > cm^U$ leads to a situation where, in case of doubt, too much rather than too little capacity is considered optimal by the CEP models.

The results presented in Figure 3 and Table 2 suggest that by performing ASP in a flexible rather than in a conventional and rigid manner by using flexible instead of conventional facility requirements, the value of airport passenger terminal facilities can be positively affected. The calculated target curve of the flexible facility requirements (blue solid line in Figure 3) is to the right of the target curves of all conventional facility requirements. This means that, across all scenarios, flexible facility requirements lead to consistently higher values of the index of merit I than conventional facility requirements. It is noticeable that the tails of the target curve of flexible facility requirements are significantly shorter than those of conventional facility requirements. This difference is particularly pronounced for the lower tails, which is an indicator that flexible facility requirements are better at mitigating and averting negative risks than conventional facility requirements. Besides that, flexible facility requirements for Check-in 1 and 3 are superior in terms of their resulting expected value of the index of merit, the VaG, the VaR, as well as the lowest and the highest observed value of the index of merit $I^{\min}$ and $I^{\max}$, respectively. For instance, the expected NPV for the flexible facility requirements is 4.9% higher than the expected value of conventional facility requirements determined with model *Fixed C*, which turned out to be the best performing conventional CEP model evaluated in this study; whilst the VaR is 7.4% higher for the flexible plan than for *Fixed C*. The financial benefits of flexible facility requirements identified in this study therefore are slightly lower than the values reported in the literature, according to which flexible engineering systems perform 10% to 30% better financially than inflexible systems (Cardin 2014; De Neufville and Scholtes 2011). The reason for this discrepancy is most likely due to the fact that the index of merit used in this study only considers the design hours in which the facilities are exposed to high levels of utilisation, which, in practice, is often associated with high (operating) costs that significantly affect the applied index of merit. In addition, a closer examination of the *Fixed C* alternative suggests a phased approach that is not too far from the most likely scenarios reported by the flexible model for the first 15 years of the planning horizon (and given the nature of NPV calculations, costs and revenues incurred further away in the future play a diminishing role in the overall result). This implies that, in practical terms, phasing developments without committing to expansion too far into the future may allow for the implementation of flexibilities 'on' systems, namely deferring or anticipating investments, even if they are not originally considered during the development of the strategic plan. Thus, real options make a key contribution to ex-post flexibility in ASP, which, according to Burghouwt (2007), refers to options for current actions only possible because of decisions taken in the past.

As stated in Table 1, the optimal decision rule for Check-in 1 and 3 is characterised by parameter vector $\boldsymbol{\theta}^* = [4, 0]$. Consequently, the facility should be expanded by $\theta_1^* = 4$ units of capacity if the difference between the observed design hour load d_t^s and the maximum possible throughput $K_t^s \cdot \mu_K$ of the facility in planning period t and scenario s is less than zero, which is given by $\theta_2^* = 0$. Indeed, the optimal expansion size θ_1^* for Check-in 1 and 3 is rather small, resulting in an average of 8.16 expansion steps of the facility across all scenarios examined. The resulting short time between two expansion steps might make the implementation of flexible facility requirements rather demanding in practice in this case. For practical applications, it could be argued that the approach used in conventional model CEP *Fixed C* represents a pragmatic and realistic implementation of a quasi-flexible plan, only with the constraint that the number of expansion steps is limited to two. As such, a truly dynamic expansion strategy as demanded by flexible facility requirements, which assume that the building space required for flexible adjustments is always readily available, places high demands on airport passenger terminal infrastructure. In practice, the required flexibility could be implemented by means of buffer spaces, which reflect the idea of reserving areas in existing passenger buildings for future developments (Butters 2010). This buffer space, which as such is a design feature of the passenger building, provides planners with real options 'in' the system, namely the option to expand Check-in 1 and 3 at any future point in time and the option to defer capacity adjustments (Chambers 2007; Kincaid et al. 2012). Because buffer spaces are usually built long before their actual conversion into a complete passenger terminal facility, they are often put to interim use, such as being used for retail or office space purposes. This way, airport operators can generate certain revenues in the meantime, which helps to justify the installation of the buffer spaces from a financial point of view. Nevertheless, it is often difficult or even impossible to identify and maintain suitable building areas in existing terminals which can be used as buffer spaces. For example, buffer space for check-in facilities exists in terminals where check-in is deployed in separate islands, as opposed to a linear setting, where desks are located at the back of the departure concourse. When check-in desks are arranged in islands, only one side of each island can be equipped with desks in the initial phase of construction, while the other side can have other interim usages. This way, future expansion can be realised by equipping the other sides of the islands with check-in desks only when demand materialises.

For greenfield projects, the construction of buffer spaces might be difficult to justify from a financial point of view. Even if in both cases it were possible to identify and/or plan with buffer spaces, an airport's management could possibly refrain from implementing facility requirements which are based on the idea of keeping building space in prime locations unused for a potentially long period of time. However, if the buffer spaces were to be put to a temporary interim use such as for retail, gastronomy, office space, or storage, the buffer spaces could yield certain revenues[11] in the period before the real option is exercised. This way, buffer spaces could be justified not only from a flexible planning perspective but also from a financial one.

The enumeration technique is used in this study to solve the presented CEP models. This solution procedure was selected as it is characterised by its simplicity and ease of implementation in a practical context. At this point, however, it must be mentioned that the enumeration technique is only suitable for CEP models with a reasonably small solution space. For CEP models with large solution spaces, such as multi-facility problems, its application is severely limited or not possible at all.[12] To ensure the efficient usage of the enumeration technique, the solution space of the CEP models introduced in this study is restricted through a series of measures. On the one hand, the planning horizon is set to $T = 20$ years and the maximum possible capacity adjustment size to $\Delta K^{\max} = 50$ check-in desks. On the other hand, the maximum number of capacity adjustments that the conventional CEP models presented in Section 4.2 can carry out within the planning horizon is limited to one for models *Fixed A and B* and two for model *Fixed C*. These measures are justifiable in the context of the ASP-related application presented in this study for a number of reasons. Firstly, strategic plans for airport passenger terminal facilities rarely cover longer planning horizons than 20 years. Furthermore, it can be assumed that Zurich Airport will not adjust the check-in facility by more than $\Delta K_t = 50$ check-in units in one single expansion step, as this would almost double the initially available capacity of $K_0 = 53$ check-in desks. Finally, most airports expand their passenger terminal facilities only a few times within a 20-year period. For example, the check-in facilities at Zurich Airport were extended twice between the years 2000 and 2023 (Flughafen Zürich AG 2023).

The flexible CEP model presented in this paper and the resulting flexible facility requirements for airport passenger terminal facilities have several implications. This study has shown that CEP models can be used by practitioners in a real-world context in ASP. The application of CEP models facilitates a data-driven planning process, which contrasts with the people-driven process often used nowadays. While today planners and managers are tasked with defining (supposedly) optimal facility requirements, this job can be delegated to CEP models in the future. Consequently, the current planning process is simplified, accelerated, and becomes less subjective. Moreover, with the application of flexible facility requirements in ASP, practitioners take over new roles; instead of determining the facility requirements themselves, they focus on the definition and parameterisation of both the CEP models and the index of merit applied, as well as the evaluation and validation of the model-generated results. Besides that, it can be argued that flexible facility requirements represent a paradigm shift in the way strategic planning for airport passenger terminal facilities is formulated and conducted. Flexible facility requirements provide a planning tool that remedies the main shortcomings of conventional ASP, which is namely the insufficient consideration of uncertainty airport planning is subject to and the definition of rigid and static, i.e. conventional, facility requirements (Burghouwt and Huys 2003; De Neufville et al. 2013; Magalhães, Reis, and Macário 2017). As such, flexible facility requirements allow for the specification of strategic plans that 'change easily in the face of uncertainty' (Hu and Cardin 2015, 122) and are 'able to modify its mode of operation or its attributes' (Saleh, Lamassoure, and Hastings 2002, 4). However, flexible facility requirements and the associated planning with real options is most likely to represent 'new territory' for most practitioners. Hence, for flexible facility requirements to be successfully used in practice, a certain willingness to learn is required on the part of the practitioners. In addition, there is also a need for management buy-in. The application of flexible facility requirements in practice most probably has an impact on the daily work of managers as their decision-making authority is affected substantially. Indeed, the actual capacity adjustment decisions are made by the (presumably optimal) decision rule. In normal operations, managers and owners should therefore not override the automatic decision-making of the decision rule, but rather take on a supervisory role.

6. Conclusion and outlook

This paper demonstrates how flexible facility requirements for airport passenger terminal facilities in the context of ASP can be created that (i) can account for uncertainty, which are typically rather substantial given the long planning horizons considered, and (ii) can flexibly adapt to ever-changing circumstances. Flexible facility requirements are determined by means of a purposely developed flexible CEP model, which has been specifically adapted to the needs and peculiarities of ASP for airport passenger terminal facilities. Particularly, two adjustments were made to the index of merit by which the facility requirements are evaluated. On the one hand, facility requirements are evaluated exclusively for all design hours of an ASP project, as this is considered standard practice in the industry. On the other hand, LoS considerations are included in the index of merit by introducing capacity mismatch costs that aim to avoid the provision of both over-capacity and under-capacity during the design hours. Based on a the application of the models to check-in facilities (Check-in 1 and 3) at ZRH Airport, it was illustrated that flexible facility requirements have a significantly higher financial value than conventional facility requirements. In addition to economic benefits, flexible facility requirements are also advantageous from a planning perspective; solely based on how the future unfolds, flexible facility requirements allow practitioners both to capitalise on opportunities as well as to mitigate or avert negative risks. In fact, given the consideration of saturated levels of demand when other elements of the airport (i.e. the runway system) constrain additional growth at peak times, the flexible alternative performs slightly better to avert negative risks than the conventional plans. However, it is worth mentioning that in a practical application, a full economic assessment must consider any potential costs associated with flexibility. For example, the installation and maintenance of buffer spaces, which, as suggested in Section 5, could enable flexibility in practice, incur costs for installation and operation, as well as to ensure it is maintained as such and not replaced with a permanent use before flexibility is exercised. Similarly, temporary uses of such buffer space may bring revenues to consider.

To better cope with the challenges the future might bring, airports would therefore be well advised to increasingly apply flexible facility requirements in practical ASP applications. Nevertheless, results of the application at ZRH Airport also demonstrate that planners and managers can learn from the advantages of flexible arrangements and incorporate them into more conventional phased developments. It was shown that the performance of the best conventional alternative matches more closely the most likely scenarios of the flexible alternative during the first 15 years of the 20-year planning horizon. Therefore, it is crucial that airport planners and managers are willing to embrace the shift in paradigm that flexible designs suppose.

Several extensions of this study are possible. First, the flexible facility requirements introduced above are based mostly on real options 'on' systems, namely the option to defer and the option to expand, whereas the buffer space can be considered a light approach to real options 'in' systems. Consequently, one could consider designing more complex decision rules that can (even) better represent real-world decision-making processes carried out at airports incorporating more sophisticated options 'in' systems, e.g. by taking more decision factors or trends into account. The solution of CEP models considering such decision rules, however, would require the utilisation of solution procedures more sophisticated than the enumeration technique. Finally, this study assumes that only passenger demand is uncertain. However, as the success of ASP is subject to many different uncertain factors, there is a need for some of these to be included in the determination of flexible facility requirements as well. For example, one could create scenarios, which describe how advances in technology, politics, and/or regulation influence the throughput rates of airport passenger terminal facilities.

Notes

1. According to Cardin (2014, 2), engineering systems are defined as 'complex systems in the aerospace, defense, energy, housing, telecommunication, and transportation industries'.
2. The method presented in this study is applicable to a wide range of types of passenger terminal facilities, such as check-in facilities, security check facilities, lounges, gates, etc. However, this circumstance does not mean that the method presented in this study allows the determination of facility requirements for more than one facility type at the same time.
3. The capacity of a given airport passenger terminal facility can never be negative, as it is impossible to have a capacity of less than 0. Furthermore, capacity, as understood in this study, is an indivisible quantity. For example, it is only possible to provide a check-in facility with a capacity of either 3 or 4 check-in desks, but not a capacity of 3.14 check-in desks.
4. Instead of *capacity mismatch costs*, Sun and Schonfeld (2015, 2016, 2017) use the term *delay costs*, as only costs resulting from congestion and delays are taken into account. This paper, however, considers not only costs incurred by the provision of too little infrastructure (which leads to delays and congestion), but also costs resulting from the provision of too much infrastructure (which is economically not justifiable). To this end, capacity mismatch costs are incurred when a facility is not considered to be optimally designed following level of service specifications by International Air Transport Association (2017). Thus, ASP-specific considerations are included in the cost function via capacity mismatch costs.
5. Note that Equation (7) is based on the assumption that all passengers passing through facility i will use it. Should the facility also be traversed by non-users, Equation (7) must be adjusted accordingly.
6. The correction factor $QF(MQT)$ is specified in International Air Transport Association (2017, 237) by means of a look-up table which specifies QF for a range of values of MQT. As this look-up table

contains proprietary information, only the *QF* value used to produce the results presented in this paper will be mentioned in Section 4.
7. The index of merit used in this study only takes design hours into account. For this reason, Equation (9) is divided by h_t.
8. Equation (11) is published in this form in International Air Transport Association (2017). Given the special form of Equation (11), the average process time must be provided in the unit seconds per passenger.
9. The available computing power defines what reasonable values for the parameters T and $\Delta K^{\max}$ are. In this study, $T = 20$ and $\Delta K^{\max} = 50$ were chosen. This resulted in a computing effort that can be handled by a normal notebook computer, see Table 1.
10. To speed up calculation, the solution of conventional CEP model *Fixed C* has been executed on 9 processor cores in parallel. All other model variants were solved on one single processor core.
11. Please note that in this study, no such buffer-related revenues were included in the *flexible* CEP model.
12. For solution procedures of CEP models with large solution space, the reader is referred to Cardin et al. (2017), Cardin, Zhang, and Nuttall (2017), Zhang and Cardin (2017) and Hu, Guo, and Poh (2018).

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No potential conflict of interest was reported by the author(s).

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Appendix. Parameterisation of CEP models

The following parameterisation has been used for the CEP models presented in this study. Unless otherwise stated, the parameters mentioned below are based on empirical values provided by the planning department of Zurich Airport Ltd.

- Number of check-in desks installed and available at $t = 0$: $K_0 = 53$
- Discount factor: $\delta = 4\%$
- Operational hours per year: $h_t = 365\,\text{days} \cdot 17\,\text{h/day} = 6205\,\text{h}$
- Temporal target LoS: $MQT^{\text{min}} = 5\,\text{min/PAX}$, $MQT^{\text{max}} = 10\text{min/PAX}$
- Correction factor QF at selected target LoS, based on IATA (2017): $QF(5min) = 0.183, QF(10min) = 0.289$
- Spatial target LoS: $A_Q = 2\,\text{m}^2/\text{PAX}$
- Required space per check-in desk: $A_K = 7\,\text{m}^2$
- Percentage of circulation space in an airport passenger terminal facility: $p_{circ} = 57.8\%$
- Peak 30-min factor: $PK = 0.5$
- Overhead costs of expansion project: $p_{ohd} = 15\%$
- Unit costs of capacity expansion and building space expansion: $ci_K = 600000\text{CHF/desk}$, $ci_A = 5000\,\text{CHF/m}^2$
- Economies of scale factor: $\alpha = 0.95$
- Unit operating costs per unit of capacity and building space: $co_K = 0.345\text{CHF/h}$, and $co_A = 0.011\text{CHF/h}$
- Average processing in check-in facility time per passenger: $PT = 60\text{s/PAX}$
- Unit throughput rate of one single check-in desk: $\mu_K = 60\text{PAX/h}$
- Unit capacity mismatch costs of over-design $cm^O = 50\text{CHF/h}$, unit capacity mismatch costs of under-design $cm^U = 50\text{CHF/h}$, coefficient of nonlinearity of capacity-mismatch-related costs $\alpha_M = 1.2$
- Unit revenue per design hour passenger $r_d = 0.1\text{CHF/PAX}$, unit revenue per unit of capacity $r_K = 7\text{CHF/h}$