CRANFIELD UNIVERSITY

MANUEL WALTERT

STRATEGIC CAPACITY PLANNING FRAMEWORK FOR AIRPORT PASSENGER TERMINAL FACILITIES

SCHOOL OF AEROSPACE, TRANSPORT AND MANUFACTURING
Transport Systems

PhD Thesis
Academic Year: 2021–2022

Supervisors: Dr R. Pagliari, Dr E. Jimenez Perez
February 2022

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Abstract

Facility requirements describe how the capacity of a facility should be adjusted over time to meet the expected future demand levels. Practitioners use them to determine the strategic development of airport passenger terminal facilities. The generation of facility requirements is extraordinarily complex, since (i) airport strategic planning is subject to high levels of uncertainty due to the extremely long planning horizons considered, and (ii) investments in infrastructure are subject to irreversibility. This study presents a strategic capacity planning framework consisting of two modules, by means of which stochastically optimal facility requirements for airport passenger terminal facilities can be determined. The demand module is applied first. Its purpose is twofold: on the one hand, to create annual aggregated demand scenarios of an airport by means of geometric Brownian motion. On the other hand, to convert these scenarios into facility-specific design hour loads with the help of linear regression models. Subsequently, the capacity expansion problem module is used to determine conventional and flexible facility requirements that maximize the net present value of an airport passenger terminal facility. For this purpose, both conventional and flexible capacity expansion problem models, presented in the literature, are adapted to the needs of airport strategic planning. Subsequently, they are solved with evolutionary optimization algorithms. The framework is applied to a real-world planning example of the existing check-in facilities at Zurich Airport. The aim of the planning example is to compare flexible facility requirements with conventional facility requirements in terms of their economic value, and to investigate how sensitive the proposed models are to variations in several input factors. The results suggest that flexible facility requirements are generally more valuable than conventional facility requirements. Moreover, the models applied in this study respond to changes in input factors in a similar way to comparable models documented in the literature.

Keywords

Strategic airport planning; capacity expansion problem; decision rules; airport passenger terminal facilities; flexible engineering systems.

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List of Abbreviations

AASP	Adaptive Airport Strategic Planning
ASP	Airport Strategic Planning
ATM	Air Traffic Movements
BHR	Busy Hour Rate
BHS	Baggage Handling System
CEP	Capacity Expansion Problem
CGDRM	Conditional-Go Decision Rule Model
CHF	Swiss Franc (currency)
CUSS	Common-Use Self-Service
CUTE	Common-Use Terminal Equipment
DCF	Discounted Cash Flow
DES	Discrete Event Simulation
DHL	Design Hour Load
DM	Decision Maker
DSP	Dynamic Strategic Planning
ENPV	Expected Net Present Value
EoS	Economies of Scale
FSP	Flexible Strategic Planning
FZAG	Flughafen Zürich AG (Zurich Airport Ltd.)
GA	Genetic Algorithm
GBM	Geometric Brownian Motion

GEP	Gene Expression Programming
IT	Information Technology
LCC	Low Cost Carrier
LoS	Levels of Service
MQT	Maximum Queueing Time
NPV	Net Present Value
PAXATM	Passenger per Air Traffic Movement (Model)
PTS	Passenger Tracking System
RFDRM	Reward Function Decision Rule Model
ROA	Real Options Analysis
SBR	Standard Busy Rate
TPHP	Typical Peak Hour Passengers
VaG	Value at Gain
VaR	Value at Risk
VoF	Value of Flexibility
WACC	Weighted Average Cost of Capital
ZRH	Zurich International Airport

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Chapter 1

Introduction

1.1 Background and problem statement

On 19 November 1999, the Spanish Ministry of Public Works and Transportation implemented the *Plan Director del aeropuerto Adolfo Suárez Madrid-Barajas* (Ministerio de Transportes Movilidad y Agenda Urbana, 1999) which is the master plan that defines the strategic development and future expansion of Madrid *Barajas* Airport up to the year 2025. Based on an inventory of the infrastructure operational in the year 1999 as well as a forecast specifying demand until the year 2025, airport planners specified in detail how the aerodrome's capacity should be adjusted in order to meet the anticipated traffic levels in the years to come. To outline the expected future demand levels, a forecast was drawn up by specialists. To this end, "future demand was forecasted as a linear, causal relationship with [gross domestic product] GDP forecasts" (Sismanidou & Tarradellas, 2017, p. 190). Based on this, planners created three different demand scenarios: a baseline scenario, an optimistic and a pessimistic scenario which differed from the baseline by +10 % or -10 %, respectively (Sismanidou & Tarradellas, 2017). In general, the demand outlook for the airport was promising; the baseline predicted a marked increase in demand from 27.5 million annual passengers in 1999 to 70.8 million annual passengers in 2025 (Ministerio de Transportes Movilidad y Agenda Urbana, 1999). For this reason, the Spanish government decided to ratify a number of strategic airport expansion projects in response to the anticipated demand levels. Among other things, the available building space of the five terminals of *Barajas* Airport was expanded to over one million square metres at a cost of 6.2 billion Euros. This expanse increased the capacity of the terminals by an additional 35 million annual passengers (Sismanidou & Tarradellas, 2017).

In retrospect, we know that the 1999 demand forecast was inaccurate at best. As illustrated in Figure 1.1, it turned out that the forecast underestimated the actual observed demand from 1999 to 2011, only to overestimate demand for the period after 2011. Subsequently, given the strategic planning decisions made in 1999, Madrid *Barajas* Airport has never been able to fully capitalise on opportunities when economic conditions were favourable. Moreover, when times changed and demand collapsed, all these expansion projects had already been implemented, leaving the airport stranded with significant overcapacity that was not justified in any way.

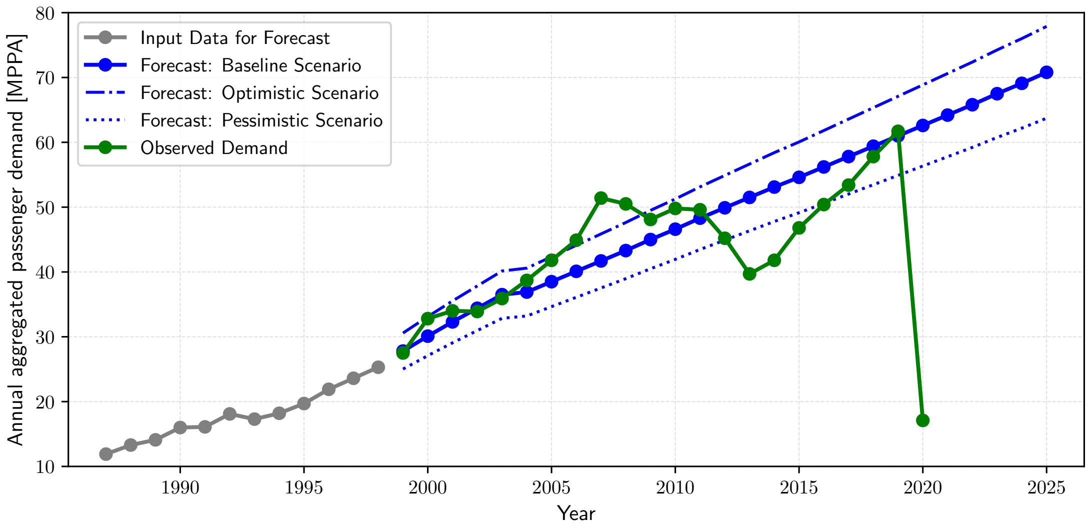

Figure 1.1: Comparison between forecasted and observed annual aggregated demand for Madrid *Barajas* Airport. Aggregated demand is expressed in million passengers per annum (MPPA). Note: Forecast data is based on information provided in Sismanidou and Tarradellas (2017), observed demand data is sourced from AENA (2021).

The 1999 master plan of Madrid *Barajas* Airport and the problems resulting thereof are a prime example that the task of capacity planning in the domain of airport strategic planning (ASP) is extraordinarily complex. A particularly demanding task is the determination of *facility requirements*, which systematically describe and quantify capacity shortfalls resulting from the imbalance between the supply and forecasted demand (Federal Aviation Authoriy [FAA], 2015, 2018; International Air Transport Association [IATA], 2017; International Civil Aviation Organization [ICAO], 1987). More precisely, facility requirements can be viewed as schedules which define when and in what fashion a specific part of the infrastructure is to be extended, re-dimensioned, or even dismantled in such a way that the expected future demand levels will be met. To create facility requirements, airport planners need two basic inputs: (i) an inventory of the operational infrastructure at the time of planning and (ii) a demand forecast describing the expected demand levels of the facilities for which the requirements are to be created.

The description of an inventory is a comparatively simple task. In fact, airport planners only have to count and categorise the operational infrastructure and quantify its capabilities, e.g. throughput rates, operating costs, etc. The preparation of a demand forecast, on the other hand, is considerably more complex. In a first step, planners often create so-called aggregated demand forecasts, which describe the expected future number of passengers or air traffic movements (ATM) per year. This aggregated "data can already be useful for the [creation] of facility requirements of [selected infrastructure], such as stands and gates, as well as the preliminary sizing of the required floor space for passenger terminals" (Waltert et al., 2021, p. 1). However, to determine facility requirements for airport passenger terminal facilities, airport planners must convert annual aggregated demand data into so-called design load demand figures. "As the term implies, design loads describe the anticipated demand levels for shorter periods of time. These time periods are determined in such a way that infrastructure is designed with sufficient capacity to process demand at a defined level of service throughout the year, avoiding the risk of overdesign in the few instances when extreme peaks may occur (De Neufville et al., 2013). Depending on the type of facility for which requirements should be defined, design loads are either specified for a day, an hour, or even shorter intervals (Kennon et al., 2016)"

(Waltert et al., 2021, p. 1). To this end, IATA (2017) and Tošić (1992) suggested to use the aggregated demand over a design hour to determine facility requirements of passenger terminal facilities such as check-ins or security checkpoints.

Given an inventory as well as a demand forecast specifying design loads, decision makers (DM) need to determine the required adaptations for the capacity of an airport passenger terminal facility over the entire planning horizon of an ASP project. In doing this, the provision of over-capacity as well as under-capacity should be always avoided. Over-capacity, which describes the provision of too much capacity, is economically not acceptable, since facilities tend to be underutilised or remain even unused over long periods of time. Needless to say, this is not a wise investment decision. Neither to be recommended is under-capacity, describing 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 delays and congestion. Consequently, airport planners must determine the exact limits of capacity for a facility over the entire planning horizon. This planning task, which is carried out not only at airports, but also for a wide range of other infrastructure, is an optimization problem known in the literature as the *capacity expansion problem (CEP)* (Luss, 1982; Martínez-Costa et al., 2014; Van Mieghem, 2003).

The most simple form of CEP considers both economies of scale (EoS) savings as well as the opportunity costs of capacity adjustments. EoS savings describe cost advantages that arise because the average unit price for infrastructure usually decreases as a function of the magnitude of the capacity adjustment. For this reason, to capitalise most on potential EoS savings, a single large capacity adjustment is most beneficial. However, investment in capacity comes with opportunity costs as well: substantial amounts of money are tied up in infrastructure, which means that it cannot be used in any other way. From this point of view, it may be more sensible to defer an investment in capacity and invest the money more profitably elsewhere. In the case of opportunity costs, not one single large project, but rather a number of small expansion projects carried out as far into the future as possible is favourable. Consequently, CEP must consider the "trade-off between the economies-of-scale savings of large expansion sizes versus the opportunity cost of installing capacity before it is needed" to determine the optimal schedule for capacity adjustments for a facility (Van Mieghem, 2003, p. 273).

The application of CEP for airports in general and airport passenger terminal facilities in particular is made more difficult by both the irreversibility of investments as well as the extremely long planning horizons that ASP is subject to. Airports and airport passenger terminals belong to a class of infrastructure which is referred to in the literature as *engineering systems*. In short, engineering systems are "complex systems in the aerospace, defence, energy, housing, telecommunications, and transportation industries" that often perform essential functions in our society and have long life cycles of 20 or more years (Cardin, 2014, p. 2). Investments in engineering systems are often irreversible; once such a system is in place, the investment costs are seldom salvageable (Dixit & Pindyck, 2012). For instance, once built, a runway or an airport terminal cannot be dismantled to be sold and rebuilt at another location. Consequently, once an investment has been made, it cannot usually be reversed or corrected in any way. Additionally, the exceptionally long planning horizons and life-cycles of engineering systems make strategic planning even more complicated. Because of the prolonged periods of time that have to be taken into consideration, one cannot predict with any certainty what the future may bring. In fact, the strategic planning of engineering systems is plagued by the uncertainty of future developments in demand, technology, politics, regulations, demographics, etc.

Based on the seminal paper of Manne (1961), a large number of *conventional CEP models*, most of which are deterministic and stochastic models proposing to solve the CEP, have been presented in the literature (Geng & Jiang, 2009; Julka et al., 2007; Luss, 1982; Martínez-Costa et al., 2014; Van Mieghem, 2003; Wu et al., 2005). Most applications of conventional CEP models focus on strategic planning applications in the manufacturing, telecommunications or service industries (Martínez-Costa et al., 2014). Few authors present applications of conventional CEP models in the context of ASP. Exemplary are Solak (2007) and Solak et al. (2009), who presented a holistic airport terminal capacity planning model, and Sun (2016) and 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 & Schonfeld, 2013), and for baggage carousels (Yoon & Jeong, 2015).

Deterministic CEP models can only deal with one single scenario of the future, while stochastic models are, to some extent, able to take into account the uncertainty which strategic planning projects is subject to. Conventional CEP models are characterised by their definition of optimal facility requirements in the form of a single capacity vector. This capacity vector specifies a precise schedule that describes when and how the capacity of the system should be changed. This is a major drawback, even for stochastic CEP models, because the conventional facility requirements determined in this process are fixed and subsequently applied to all future scenarios, irrespective of how they actually develop. 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 et al., 2018, p. 254). For this reason, facility requirements are needed that are able to adapt flexibly to changing circumstances. Or in other words, facility requirements that are not identical for all future scenarios, but can be adapted individually.

To introduce flexibilities in the strategic planning of engineering systems, Trigeorgis (1996) suggests the application of *real options* which "[represent] a right, but not an obligation ... to do something at [*sic*] under predefined arrangements" at a future point in time (De Neufville, 2003, p. 7). Real options are either 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), or design features that are intentionally built into engineering systems with the aim of allowing for physical changes of the system itself (Wang & De Neufville, 2005). Real options have proven to be valuable, since they enable system owners and DM both to capitalise on future opportunities as well as to mitigate or avert negative risks based on how future uncertainty turns out (Cardin, 2014; De Neufville, 2000). Indeed, the literature reports that flexible system designs perform between 10 % to 30 % better financially than inflexible, i.e. conventional, system designs (De Neufville & Scholtes, 2011).

Unfortunately, real options cannot be integrated into conventional CEP models. Even though conventional CEP models can determine stochastically optimal facility requirements which consider uncertainty to a certain degree, conventional models consider only "passive management" (Schachter & Mancarella, 2016), which results in rigid capacity adjustment schedules that are not able to "adapt if the actual situations do not follow the modelled scenarios" (Cardin & Hu, 2016, p. 2). Just recently, however, a few authors have extended conventional CEP models to *flexible CEP models* which allow the generation of stochastically optimal flexible facility requirements by means of real options. Flexible CEPs have been applied to a number of different engineering systems, such as multi-storey car parks (De Neufville et al., 2006), nuclear power plants (Cardin, Zhang et al., 2017), on-shore liquid natural gas production facilities (Cardin et al., 2015), emergency medical services infrastructure (Zhang & Cardin, 2017) or waste-to-energy systems (Cardin & Hu, 2016; Cardin, Xie et al., 2017; Hu et al., 2018; Xie et al., 2014; Zhao et al., 2018). To the author's 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.

1.2 Aim and objectives

In the light of these gaps in the literature, this study aims to develop, test and apply a strategic capacity planning framework which enables airport planners and DM to determine optimal facility requirements for airport passenger terminal facilities in the context of ASP. This planning framework consists of two main modules:

(i) a demand module; this is used to determine future aggregated annual demand scenarios for an airport and also to convert these aggregated figures into design hour loads for airport passenger terminal facilities.

(ii) a CEP module; this is used to determine stochastically optimal facility requirements for airport passenger terminal facilities.

Subsequently, the objectives of this study are:

(i) to examine, develop, test and apply a methodology which allows to both determine annual aggregated demand forecast scenarios for an airport, as well as to convert these numbers into the design hour loads (DHL) of individual airport passenger terminal facilities;

(ii) to examine, develop, test and apply a methodology which allows to determine stochastically optimal facility requirements for airport passenger terminal facilities in the context of ASP;

(iii) to apply the proposed strategic capacity planning framework to a real-world planning example in which conventional and flexible facility requirements for a check-in facility at Zurich International Airport (ZRH) Airport are determined;

(iv) to compare flexible facility requirements for existing check-in facilities at ZRH Airport with conventional facility requirements in terms of their economic value;

(v) to investigate which factors influence conventional and flexible facility requirements for the check-in facilities at ZRH Airport and also the extent of this influence.

1.3 Original contributions

This study contributes to science in a number of ways:

(i) It presents an annual aggregated demand model which enables airport planners to sample a large number of plausible future passenger demand scenarios. The suggested approach is not per se a novel concept, but rather an application of existing methods from the field of engineering systems literature in the context of ASP.

(ii) A ratio-based design hour model is put forward. This model enables the efficient conversion of annual aggregated demand forecast scenarios into design hour load forecasts for airport passenger terminal facilities. The proposed method makes use of real, disaggregated and automatically collated (big) input data describing passenger flows in airport terminals. These two concepts, the ratio-based model for the determination of the DHL of individual passenger terminal facilities and also the means by which input data is collected and processed can be considered scientific innovation. A scientific article in the *Journal of Air Transport Management* has been published for this part of this study, see Waltert et al. (2021).

(iii) Conventional and flexible CEP models presented in the literature are adapted for appropriate use in the context of ASP for airport passenger terminal facilities. While conventional CEP models have been used for ASP-related purposes, the application of flexible CEP models to determine stochastically optimal flexible facility requirements for airport passenger terminal facilities is a scientific novelty.

(iv) The proposed strategic capacity planning framework for airport passenger terminal facilities is applied in a relevant planning example in order to determine facility requirements for existing check-in facilities at ZRH Airport. In the course of this planning example, flexible facility requirements are compared with conventional facility requirements in terms of their economic value as well as their sensitivity to variation in several factors, such as demand and technology.

1.4 Scope of thesis

This study is application-oriented: the strategic capacity planning framework presented in this work has been developed with practical applications in the field of ASP in mind.

To this end, a quantitative strategic planning approach for the determination of optimal facility requirements of airport passenger terminal facilities is put forward. As such, all the models presented in this study aim to assist practitioners in their daily work, be they airport planners, managers and decision makers. The mathematical methods employed, in particular the solvers and solution procedures required for the CEP models, have been applied from the airport planner's point of view. Therefore, this work does not aim to further develop the theoretical foundation of the methods applied, but rather to describe their application in the context of ASP. By means of a planning example, which is based on the determination of optimal facility requirements for existing check-in facilities at ZRH Airport, the models presented are applied, tested and validated. In doing so, a relevant example is used to illustrate how the proposed strategic capacity planning framework can be applied in practice.

1.5 Thesis structure

The study is organised as follows: Chapter 2 provides an overview of the literature pertaining to a strategic capacity planning framework for airport passenger terminal facilities. To this end, the literature review covers the areas of ASP in general, the modelling of design hour load demand, the notion of flexibility in engineering systems, the recognition and modelling of uncertainty, as well as the evaluation and selection of facility requirements by means of conventional and flexible CEP models. The research questions of this study, which pertain to three different research areas, are presented in Chapter 3. Subsequently, Chapter 4 sets out the methodology for the proposed strategic capacity planning framework for airport passenger terminal facilities. This chapter is divided into 4 parts, each of which deals with one component of the proposed strategic capacity planning framework. These are: (i) the annual aggregated demand model, which is used to create demand scenarios for airports, (ii) the DHL model, which is used to convert the annual aggregated demand scenarios into facility-specific DHL scenarios, (iii) the valuation model, which allows the objective economic evaluation of facility requirements, and (iv) capacity expansion problem models, which can be used to determine both optimal conventional and optimal flexible facility requirements for airport passenger terminal facilities. In Chapter 5, the strategic capacity planning framework is then applied to a real-world planning example on check-in facilities at ZRH Airport. The main findings of this study and their implications are discussed in Chapter 6. Finally, Chapter 7 both summarises and concludes this study as well as highlights opportunities for future research.

Chapter 2

Literature review

This chapter reviews the relevant literature in four sections. Section 2.1 provides an overview of classical and flexible approaches taken to conduct ASP, followed by an in-depth discussion of the processes applied to determine facility requirements for airport passenger terminal facilities. The theoretical background to the topics of engineering systems as well as real options, which are the actual building blocks of flexible infrastructure, are discussed in Section 2.2. Section 2.3 addresses the recognition and modelling of uncertainty. Here, the focus is on the creation of demand scenarios for airports and airport passenger terminal facilities. These scenarios serve as the input for conventional and flexible CEP models which are then used to determine stochastically optimal facility requirements for airport passenger terminal facilities. The actual processes, methods and techniques applied to evaluate and finally select which facility requirements are *optimal*, are reviewed in Section 2.4. Here, the methods applied in both conventional and flexible CEP models are discussed. Finally, Section 2.5 identifies and summarises the gaps in the literature.

2.1 Airport strategic planning

The environment in which airports operate is constantly evolving. These circumstances have a direct influence on the "size, quantity, and type of airport facilities needed to accommodate future demand" (FAA, 2015, p. 48). The processes which describe how airports adapt to new conditions are usually summarised under the term *airport planning*. More specifically, airport planning is conducted on three different *decision levels* referring to distinct time horizons, the operational level, the tactical level and the strategic level. According to Shuchi et al. (2012), operational airport planning covers planning activities which are carried out on a daily or weekly basis and have a direct impact on current operations, such as the scheduling of staff or infrastructure opening times. Tactical planning encompasses a time horizon of 2 to 5 years (Shuchi et al., 2012) and deals with capacity adjustments within existing facilities, buildings or airport perimeters (Magalhães et al., 2020). Strategic planning is defined by De Neufville et al. (2013, p. 83) as a "disciplined process for analysing the current situation of a business activity, and identifying the vision of how that entity should position itself regarding its customers and competitors". Hence, strategic planning is strongly linked to an enterprise's business strategy in such a way that decisions carried out under strategic planning activities have a direct impact on the future shape of an organisation and its business model (Kwakkel et al., 2008). Thus, ASP can be regarded as an umbrella term for all activities airport operators or regulatory bodies take in order to define the future perimeter, shape, function and form of an aerodrome on a planning horizon of typically 20 to 50 years (FAA, 2015; IATA, 2017; ICAO, 1987; Shuchi et al., 2012). This comprises decisions on how facilities should be extended, expanded or, if need be, decommissioned (Magalhães et al., 2017, 2020). As a means of conducting ASP, the literature distinguishes two different planning doctrines: the *classical* ASP approach and the *flexible* ASP approach, both of which are discussed in more detail in the next section.

2.1.1 Classical and flexible airport strategic planning approaches

The classical ASP approach, also known as *master planning*, is discussed in detail by FAA (2015), IATA (2017) and ICAO (1987). As such, a master plan "presents the planner's conception of the ultimate development of a specific airport" (ICAO, 1987, p. 1–2). In other words, a master plan describes how an existing aerodrome should be adjusted, or a greenfield site built, so that future demand levels can be properly met with the appropriate levels of capacity throughout the whole planning horizon.

There is no universally accepted definition of the master planning process in the literature. However, virtually all authors describe the planning process in a similar way. For example, a detailed overview of the master planning process is given in IATA (2017), which is then summarised and simplified by De Neufville et al. (2013) in the following five steps:

(i) *Inventory.* The inventory or *site evaluation* is the basis of any master planning project. For an inventory, airport planners compile a detailed description of the current state of existing airport infrastructure (De Neufville et al., 2013; IATA, 2017). According to IATA (2017), an inventory consists of an evaluation of the conditions of both the physical and non-physical characteristics of all the facilities (FAA, 2018), an assessment of the current service conditions and levels of service provided as well as an analysis of the capacity of these facilities. For instance, for an airport passenger terminal facility, planners gather information on the available number of servers, desks, service lanes, the building space used for queues, waiting and circulation, the costs of operation and maintenance or the remaining useful life of facilities (IATA, 2017). At the same time, areas of the airport which are well suited for future expansions or extensions are identified in the inventory.

(ii) *Demand Forecast.* ASP activities are usually based on (an) annual aggregated demand forecast(s), which specify the expected annual levels of future traffic in terms of total passengers and ATMs. Demand forecast data is provided for the entire planning horizon of an ASP project, which is referred to in this study as T. The planning horizon is usually divided into a finite number of planning phases $t = 1,2,\ldots,T$. In classic ASP, a *point forecast*, which describes the single most probable future demand outlook for every planning phase $\mathbf{D} = [D_1, D_2, \ldots, D_T]$, is elicited and subsequently used.

(iii) *Facility Requirements.* Facility requirements describe and quantify capacity shortfalls which result from the imbalance between the supply of capacity (identified by means of the inventory) and future levels of demand (described by means of demand forecasts) for airport facilities (FAA, 2015, 2018; IATA, 2017; ICAO, 1987). More specifically, facility requirements can be viewed as schedules which define when and in what fashion a specific part of the infrastructure is to be adjusted by means of expansions, extensions or reductions of capacity (FAA, 2015; IATA, 2017).

(iv) *Development of Alternatives.* An alternative describes one viable way of implementing the facility requirements identified without being a detailed construction plan (ICAO, 1987). For instance, airport planners might consider various terminal configurations, such as linear concepts, pier concepts, satellite concepts, etc., or buildings with different numbers of storeys as different alternatives. The development of alternatives depends heavily on a number of strategic choices, such as the business strategy of an airport, governmental policies, regulations, environmental constraints, the business model of the home base carrier, market entries of new airlines, technological advances, etc.

(v) *Selection.* All the alternatives generated in step (iv) are evaluated in terms of their operational, environmental and financial impacts. Subsequently, airport planners select the most viable alternative for future implementation. For this option, a so-called *development plan* – also known as the *master plan* – is outlined. This master plan provides detailed information on how and when exactly this option can be implemented (IATA, 2017).

The classical ASP process is used at various airports and can therefore be considered an industry standard. The 1999 master plan of Madrid *Barajas* Airport presented in Chapter 1 is a prime example of strategic plans determined by means of the classical ASP process. Despite its frequent use in practice, however, scholars criticise classical ASP as being "fundamentally flawed", "unrealistic", "irresponsible" (De Neufville et al., 2013, p. 82) or "inadequate" (Burghouwt & Huys, 2003, p. 41). It is argued that master planning in its original form leads to a "fairly static view of the industry" (De Neufville, 2008, p. 37), something which "cannot be justified" in our very dynamic world of today (Burghouwt & Huys, 2003, p. 41). Here, two main points are criticised in the literature, namely (i) the need to include uncertainty in classical ASP and (ii) the lack of flexibility of the master plan itself.

Classical ASP does not explicitly consider uncertainty. In fact, classical ASP is based on the single most probable forecast of the future in terms of traffic levels, technology, political or social developments, etc. This approach is criticised in the literature because there is much evidence to show that long-term planning is strongly affected by uncertainty. For instance, medium and long-term demand forecasts covering planning horizons of 5 to 10 years routinely differ from the actual traffic development by 20 % or more (De Neufville et al., 2013; Nishimura, 1999). For longer planning periods, Maldonado (1990) reports forecast errors in the range of 34 % to 210 % for demand outlooks covering 15 years. Furthermore, according to Walker et al. (2013), forecasts do not consider sudden changes and disruptions of a trend, such as the 9/11 terrorism attacks (Blunk et al., 2006) or the COVID-19 pandemic (Sun et al., 2020), both of which resulted in a significant global economic downturn. For these reasons, scholars argue that point forecasts should always be considered "wrong" (De Neufville, 2008; De Neufville et al., 2013; Flyvbjerg et al., 2003).

In addition to the inadequate or even lack of consideration of uncertainty, the actual structure of the master plan is also criticised in the literature. A master plan can be seen as a blueprint that defines exactly how and when an airport is going to be developed further in the future. Such a linear document, however, is rigid and does not allow DMs and planners to flexibly respond to new circumstances without impairing the entire planning. Therefore, the literature calls for the definition of strategic plans that are designed and formulated in such a way that they can be flexibly adapted to constantly changing conditions without having to be drawn up from scratch every time (Magalhães et al., 2017).

Indeed, to remedy the shortcomings of classical ASP, the literature suggests the introduction of flexible ASP methods which take into account uncertainty as well as allowing for the definition of flexible strategic plans. In this kind of process, uncertainty can be included by considering not only one single point forecast but rather a (very large) number of different scenarios of the future, of which "neither [no] one [is] more plausible than the other" (Chambers, 2007, p. 60). Furthermore, by means of flexible ASP, airport infrastructure which "enable[s] the airport owners to respond easily and effectively to the range of scenarios that might occur" is put forward (De Neufville, 2008, p. 53). As a result, flexible planning is adjustable and capable of adapting to new circumstances (Burghouwt, 2007; Kwakkel et al., 2008) at the "maximum value for money of investment used" (Magalhães et al., 2017, p. 377).

The literature review on flexible ASP approaches presented by Magalhães et al. (2017) lists three distinct planning methods that enable the determination of flexible plans: dynamic strategic planning (DSP), flexible strategic planning (FSP) and adaptive airport planning (AASP). DSP is proposed by De Neufville et al. (2013) as a fully compatible add-on to the classical ASP process presented above. Rather than relying on point forecasts, DSP considers a large number of different scenarios which describe probable futures. Furthermore, instead of defining fixed facility requirements covering the entire planning horizon as described in the classical ASP process, only so-called first-phase capacity developments are determined in DSP. This refers exclusively to infrastructure changes that can be implemented immediately or in the near future. All other decisions regarding capacity adjustments will be made at a later date. In this way, planners are capable of constantly adapting both their planning as well as the operational infrastructure to the current needs of an airport.

Similarly to DSP, Burghouwt (2007) and Burghouwt and Huys (2003) suggest FSP as a flexible ASP concept complementary to the master planning process. To this end, FSP includes a number of methods enabling flexibility, such as real options, multi-future robustness and back-casting, contingency planning, scanning and experimentation or diversification (Burghouwt, 2007). According to Magalhães et al. (2017), FSP can be seen as an evolution of DSP, which, however, has not been applied to real-world, practical ASP projects yet (Kwakkel et al., 2010).

Kwakkel et al. (2008), Kwakkel (2010) and Kwakkel et al. (2010, 2012) introduce AASP, which is a flexible ASP approach based on the *stepwise adaptive policy-making* approach presented by Walker et al. (2001). As such, adaptive policy-making describes a planning process in which organisations or individuals continuously "apply new information and ideas to policy" (Busenberg, 2001, p. 173). Therefore, AASP is based on an initial basic policy, which, if need be, is subsequently modified with predefined *potential actions* in response to current developments in demand, technology, politics, the environment, etc. (Kwakkel et al., 2010).

Irrespective of whether a classic or flexible ASP approach is applied, the definition of facility requirements requires the availability of an inventory of the operational infrastructure as well as (a) forecast(s) specifying the anticipated future development of demand and other factors. For this reason, the next section focuses on facility requirements in more detail.

2.1.2 Facility requirements

Airports aim to provide always exactly the right amount of capacity over the entire planning horizon of an ASP project. Thus, airport operators attempt to avoid mismatches between the supplied capacity and that actually required by finding the optimal trade-off between the provision of *over-designed* and *under-designed* capacity. Over-designed capacity describes the condition when more infrastructure is made available than would actually be needed to handle demand. This leads to under-utilised infrastructure, since, even during peak times, parts of the facility are likely to remain unused. Clearly, the provision of over-designed capacity is not acceptable from an economic point of view. In contrast, under-designed capacity describes the situation when too little infrastructure is made available and when an airport or a facility, especially during peak times, is unable to maintain the service quality promised to stakeholders, e.g. average waiting time per passenger, building area provided to each passenger, etc. The consequence of under-designed capacity may be an increased probability of congestion and delays, which airport operators usually want to prevent as much as possible.

To avoid capacity mismatches, airport operators can either take short-term or long-term measures. In the short-term, airport operators can introduce, adapt or improve the allocation of capacity to users by regulating the access to the airport by means of slots, fees or taxes (Oum et al., 2004; Oum & Zhang, 1990; Zhang & Zhang, 2010). There is also some further leeway by optimizing the allocation of staff. Physical adjustments of airport capacity, however, can usually only be made as long-term measures, as changes to the infrastructure are always associated with (sometimes very) long lead times (Xiao et al., 2013). This study will only consider long-term capacity adjustments. Short-term capacity adjustments are expressly not addressed with any further mention.

In order to plan the long-term capacity development of an infrastructure, airport planners specify so-called facility requirements. Facility requirements can be viewed as schedules which, based on the quantification of capacity shortfalls resulting from imbalances between the future demand and supply for airport infrastructure, describe when and how existing facilities shall be adjusted (FAA, 2015, 2018; IATA, 2017; ICAO, 1987). In this context, this study distinguishes between *conventional facility requirements* and *flexible facility requirements*.

Conventional facility requirements for an airport passenger terminal facility can be viewed as schedules which define when and how the capacity of the facility should be adjusted by means of expansion and extension or, if need be, the decommissioning and removal of existing infrastructure. Facility requirements could theoretically be defined in such a way that capacity can be continuously adjusted over the entire planning horizon. However, to simplify the determination of facility requirements, time is often discretised into a finite number of *planning phases* $t = 0, 1, \ldots, T$, where T refers to the *planning horizon* of the ASP project and $t = 0$ to the initial conditions which all planning activities are based upon. Consequently, conventional facility requirements for an airport passenger terminal facility i can be formally described with a capacity vector $\mathbf{K}_i = [K_{i,1}, K_{i,2}, \ldots, K_{i,T}]$. The elements $K_{i,t}$ of this vector specify the operational capacity of facility i in planning phase t, e.g. 5 check-in desks or 2 security checkpoints in planning phase 3. Once conventional facility requirements are created, they cannot be adapted to changing circumstances. If future conditions are different from those assumed during planning, the entire planning process has to be undertaken again. Thus, flexible facility requirements must be created for the purpose of flexible planning.

The definition of *flexible facility requirements* is a more complex matter. Instead of defining capacity vectors, flexible facility requirements are usually formulated as *decision rules* (Cardin, 2014; Cardin & Hu, 2016; Cardin, Xie et al., 2017). A decision rule is a guideline for airport planners and DMs which prescribes exactly how the infrastructure is to be modified should certain factors, such as demand, change. Because it is only a decision rule and not a predefined capacity vector which is specified, flexible facility requirements can take uncertainty into account. As a result, flexible facility requirements allow the creation of plans that are adaptable to changing circumstances.

In light of the above-mentioned trade-off between the provision of over-designed and under-designed capacity, airport planners are interested in determining *optimal* facility requirements. To this end, the literature considers a facility requirement as optimal, when it leads either to a maximum net present value (NPV), to maximum profits or to minimum costs over the entire planning period (Martínez-Costa et al., 2014). The definition of optimal facility requirements is not a simple matter. It is an optimization problem known in the literature as the *capacity expansion problem* (CEP) (Freidenfelds, 1981; Manne, 1961; Martínez-Costa et al., 2014; Van Mieghem, 2003).

The models used to solve the CEP are collectively referred to as CEP models. *Conventional CEP models* are reviewed in Section 2.4.3 and *flexible CEP models* are discussed further in Section 2.4.4. The remainder of this section discusses the input required for conventional and flexible CEP models; these are level of service (LoS) and DHL demand.

LoS determines how much capacity is needed so that, given a certain volume of traffic, a facility is neither considered over-designed nor under-designed. DHL, on the other hand, describes the traffic levels used by airport planners to size and design airport facilities.

2.1.3 Levels of service

According to De Neufville et al. (2013, p. 564) "[LoS] refers to the quality of the context in which a service takes place". Following Martel and Seneviratne (1990) and Seneviratne and Martel (1991), a number of different qualitative and quantitative performance measures can be used to describe the service level provided in airport passenger terminals and facilities (Correia & Wirasinghe, 2004; De Neufville et al., 2013; FAA, 2018). Qualitatively, descriptors which are somewhat subjective, such as the cleanliness of a facility, the level of safety, the passenger comfort experienced, the information provided to passengers or the complexity of the procedure(s), may contribute to the perceived quality of service. Quantitatively, the quality of service can be objectively measured with a number of performance indicators, such as the waiting times experienced, average processing and service times, queue lengths, passenger densities, the level of congestion, the available number of seating options, walking distances, walking speeds, etc.

As pointed out by Correia and Wirasinghe (2004, p. 5), almost all qualitative and therefore subjective LoS measures presented in the literature are insufficient, since they (i) "cannot assess the passenger perceptions about these values" and (ii) are not capable of providing reasonable correlations between qualitative and quantitative performance measures for airport passenger terminal facilities. Therefore, given the sheer complexity of the concept of quality of service, most airport planners apply LoS measures which are based on quantitative measures only (Correia & Wirasinghe, 2004). In fact, the quantitative LoS measures proposed in IATA's *airport development reference manual* find widespread application in most real-world airport terminal planning projects (IATA, 2017). For this reason, IATA's LoS measures are often considered the de facto industry standard (Ashford et al., 2013; De Neufville et al., 2013; Kazda & Caves, 2007).

The LoS concept used by IATA (2017) is based on research conducted by the Highway Research Board in the United States (National Academies of Sciences, Engineering, and Medicine, 1965), which focused on specifying levels of service for highways by describing the relationship between the observed average speed of cars and the rate of flow on the highway. In a similar manner, IATA (2017) defines service quality for airport passenger terminal facilities using two different metrics, namely spatial and temporal LoS standards. While spatial standards define the relationship between space available per passenger with the level of service actually experienced, temporal standards refer to acceptable waiting times experienced by passengers. In essence, IATA (2017) expresses spatial and temporal LoS in terms of three distinct categories: *over-design*, *optimum* and *sub-optimum*. For instance, a check-in facility meets an *optimal LoS* standard, i.e. an optimum LoS category, if the facility is designed in such a way that during its design hour (see Section 2.1.4) passengers experience an average queueing time between 10 min to 20 min, and are provided with 1.3 m^2 to 1.8 m^2 terminal space on average while queueing (IATA, 2017). If passengers experience longer waiting times and/or are provided with less queueing space, the facility is considered to be sub-optimal. On the other hand, a facility is over-designed if shorter waiting times are observed and/or more queueing space per passenger is provided. Consequently, IATA (2017) advises airport planners to design and size airport passenger terminal facilities in such a way that the both the observed temporal and spatial LoS standards meet the optimal *target LoS*.

Target LoS standards are often subject to contractual agreements between airports and their partners, e.g. handling agents, airlines, etc. For this reason, target levels of service cannot usually be influenced by planners, but must rather be accepted as given. Consequently, planners must determine the capacity level of a facility at which, given a certain traffic volume, the target LoS can be met. In order to do so, practitioners have several methods at their disposal, such as analytical queueing models, rule-of-thumb models, discrete-event simulation models, agent-based simulation models and system dynamics models. These models are all described in the following paragraphs.

Analytical queueing models are based on queueing theory (Fitzsimmons et al., 2008; Hopp & Spearman, 2011; Newell, 2013), which allows the prediction of the average queue lengths and waiting times in passenger terminal facilities in steady state conditions. For ASP applications in the area of passenger terminal facilities, holistic models covering the entire terminal or numerous passenger terminal facilities (Andreatta et al., 2007; Brunetta et al., 1999; McKelvey, 1988), as well as facility-specific models, such as for gates (Chen & Schonfeld, 2013), check-in (Bevilacqua & Ciarapica, 2010), security checkpoints (Dorton & Liu, 2016; Hu & Chen, 2017) or baggage claim areas (De Barros & Wirasinghe, 2004) are mentioned in the literature.

Rule-of-thumb models are empirical in nature, as they are based on years of observation and experience. Probably the most important contribution to the body of literature on rule-of-thumb models is provided in IATA (2017). IATA's model allows the determination of the required capacity level of an airport passenger terminal facility given temporal and spatial target LoS and DHL demand levels. While rule-of-thumb models find wide application in the industry, they have only been rarely used in academia, such as in Nõmmik and Antov (2017).

Discrete event simulation (DES) models enable to model dynamic processes and systems by means of the description of a sequence of events which modify the state of the system accordingly. An event may occur at a certain point in time which triggers the transition from one state of the system to another one (Cassandras & Lafortune, 2009; Law et al., 2000). For airport passenger terminal applications, the literature lists holistic DES model applications, such as in Beck (2011), Brunetta and Jacur (1999), Gatersleben and Van der Weij (1999), Guizzi et al. (2009), Hee and Zeph (1998), Lim (2008), Verbraeck and Valentin (2002) and Yamada et al. (2017), as well as facility-specific applications, such as for check-in (Appelt et al., 2007; Joustra & Van Dijk, 2001), security checkpoints (Dorton & Liu, 2016; Kierzkowski & Kisiel, 2017; Pendergraft et al., 2004; Van Boekhold et al., 2014; Wilson et al., 2006) or waiting rooms (Ju et al., 2007).

In agent-based models (Bonabeau, 2002; Law et al., 2000), the dynamics of systems are reproduced by considering a number of autonomous agents, such as passengers, pieces of luggage or vehicles, which move through a passenger terminal or a facility. Agent-based passenger terminal models are presented by Fonseca i Casas et al. (2014), Ma (2013), Ma et al. (2011) and Schultz and Fricke (2011).

Finally, system dynamics models (Forrester, 1994; Sterman, 2002) are continuous simulation models in which the state of a system is modelled continuously over time, usually by means of differential equations. In the field of airport passenger terminals, system dynamics models are presented by Manataki and Zografos (2009a, 2009b, 2010) and Suryani et al. (2010).

Complex models such as discrete event simulation models, agent-based models and, to a certain extent, system dynamics models, allow airport planners to analyse airport passenger terminal processes and facilities at high levels of detail. However, this level of detail implies that the models require large numbers of input factors and are also often very intensive computationally. In contrast, analytical queueing models and rule-of-thumb models are based on simplifications, generalisations and assumptions, which both reduce the requirements on the input factors and enable faster calculation times. In the domain of ASP, where large numbers of different future scenarios must be analysed in an efficient manner, the use of such simple models can be advantageous compared to complex models, due to their simplicity, flexibility to adapt to different scenarios, faster run-times, and the limited number of required inputs (Janic, 2007). Moreover, given the large extent of uncertainty which ASP is subject to, the imperfections and simplifications introduced by simple models are usually negligible. For this reason, it is easy to understand why simple rule-of-thumb models, such as the capacity model published in IATA (2017), are very popular in the industry.

2.1.4 Design hour loads

In addition to a defined target LoS, airport planners need information on the expected future demand levels for an airport passenger terminal facility so that corresponding facility requirements can be created. For most ASP projects the first step is, as mentioned in Section 2.1.1, to create aggregated demand forecasts. However, for the design, planning and sizing of airport passenger terminal facilities these aggregated figures must be converted into so-called *design load* demands (Ashford et al., 2013; De Neufville et al., 2013; IATA, 2017; Landrum & Brown et al., 2010). In this context, Waltert et al. (2021) state the following:

> As the term implies, design load describes [*sic*] the anticipated demand levels for short periods of time. These time periods are determined in such a way that infrastructure is designed with sufficient capacity to process demand at a defined LoS throughout the year, avoiding the risk of over-design in the few instances when extreme peaks may occur (De Neufville et al., 2013). Depending on the type of facility for which requirements should be defined, design loads are either specified for a day, an hour or even shorter intervals (Kennon et al., 2013). Interestingly, there is no standard method to determine design load that is universally accepted by researchers and practitioners (Ashford, 1988). Often, the selection of a specific method depends on the individual preferences of the airport operator, authorities and other stakeholders.
>
> In fact, to determine facility requirements of passenger terminal facilities, a DHL, which is the aggregated demand over the period of the design hour, is normally used (IATA, 2017; Tošić, 1992). A number of different definitions for DHL exist in the literature (De Neufville et al., 2013; FAA, 2018; IATA, 2017; ICAO, 1987; Kennon et al., 2013; Kincaid et al., 2012). Definitions which are widely used are the standard busy rate (SBR), the busy hour rate (BHR) or the typical peak hour passengers (TPHP). The SBR is defined as the "30$^{\text{th}}$ highest hour of passenger flow … [which is the flow] that is surpassed by only 29 hours of operation[s]" for the entire year (Ashford et al., 2013, p. 32). The BHR is the "busiest hour for which the cumulative

> hourly traffic exceeds 5 per cent of the annual traffic" (Psaraki-Kalouptsidi, 2010, p. 141) and the TPHP is defined as "the peak hour of the average peak day of the peak month" (Ashford et al., 2013, p. 34). Given these different definitions of DHL, practitioners are recommended to select an appropriate measure with care. Indeed, research indicates that, for instance, the BHR is a more robust measure than the SBR, since "the percentages of passenger encountering flow rates greater then [*sic*] the SBR can easily vary from under 2 % at large airports to over 10 % at smaller ones" (Matthews, 1995, p. 58). (pp. 1–2)

Waltert et al. (2021) further explain that:

> ... [t]o define the relationship between DHL for airport terminal facilities and annual demand, it is necessary to understand the underlying demand functions, which describe how the facilities are frequented by passengers. Airport passenger terminals are complex systems consisting of a set of facilities (e.g. check-in, security checkpoints, emigration, immigration, baggage claim areas, etc.) which are frequented by a number of different passenger flows. Large hub airports usually accommodate different types of passenger flows, such as local and transit, as well as domestic and international. While local passengers either commence or terminate their journey at the airport, transit passengers only change airplanes. Domestic passengers are not subject to passport control or customs checks, while for international passengers usually the opposite is true[1]. Similarly, transit passengers are usually not required to use check-in facilities, and in case of passengers connecting between arriving and departing domestic flights, neither passport control nor immigration checks are required. For this reason, each passenger terminal facility is subject to an individual demand function, which, due to downstream

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

propagation of passenger flows, strongly depends on demand functions of other facilities in terms of magnitude, mix and timing. Therefore, the demand function of a passenger terminal facility is an amalgam of different passenger flows scheduled to use the facility. Consequently, this makes the estimation of the DHL for an individual passenger terminal facility especially challenging. To this end, the literature mentions two distinct methods to estimate DHLs for passenger terminal facilities: (i) the design day schedule method, and (ii) the ratio method.

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

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

$$d_{i,t} = \rho_i D_t \tag{2.1}$$

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

$$d_{i,t} = f(D_t, \beta_i) + \varepsilon_t \tag{2.2}$$

where β_i is a vector of unknown coefficients and ε_t is an error term. The unknown ratio ρ_i in [Equation 2.1] and the unknown coefficients β_i of [Equation 2.2] are estimated with an appropriate approximation method, such as the least squares method. In order to do so, a (large) dataset of historic observations for both the DHL $d_{i,t}$ of facility i and the annual demand D_t for a number of years $t = 1, 2, \ldots, T$ is required. Once these unknown coefficients of a ratio-based model are estimated, it can be subsequently used by airport planners to translate future annual demand forecasts into DHL forecast figures with relative ease.

Due to its simplicity, the ratio-based method has been widely used in airport strategic planning, especially for passenger terminals. For instance, in FAA advisory circular 150/5360–7 (cancelled) produced a series of constant ratios between the TPHP and annual passenger volumes for US airports. Similarly, the UK Civil Aviation Authority defined a number of constant ratio values which specify the SBR measure as a function of ATM (Ashford et al., 2013). See Table 2.1 for a summary of commonly used figures.

Matthews (1995) suggested a linear model to forecast peak hour demand at airports operated by the British Airport Authority (BAA, now operating

Aggregated annual passengers D_t	ρ as % of annual demand
$\geq 30.000 \times 10^6$	0.035
$20.000–29.999 \times 10^6$	0.040
$10.000–19.999 \times 10^6$	0.045
$1.000–9.999 \times 10^6$	0.050
$0.500–0.999 \times 10^6$	0.080
$0.100–0.499 \times 10^6$	0.130
$\leq 0.100 \times 10^6$	0.200

Table 2.1: Typical peak hour passengers as defined in FAA AC 150/5360-7 (cancelled). Note: Adapted from Ashford et al. (2013, p. 34).

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

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

The ratio method, as it is presented in the literature, treats the airport and its underlying systems as *blackboxes* for which no prior knowledge is required for the modelling process. In fact, since it is a purely data-driven method, simply a large enough number of historic observations on annual demand and DHL are required to determine appropriate ratios or to estimate the coefficients of a regression model. However, in the context of emerging markets, where growth levels can be quite exceptional, historic observations are only of limited value to describe future demand. For any given airport, as annual demand volume grows, the absolute peak loads become less pronounced since demand is more equally distributed over time (De Neufville et al., 2013; IATA, 2017). Moreover, for many airports the total number of ATMs per year is limited due to constraints imposed for operational, legal, environmental or political reasons, which leads to saturation effects. For instance, the runway configuration of an airport, which determines the available number and orientation of runways, defines the absolute maximum annual ATM that can be accommodated (FAA, 2015; ICAO, 1987). Indeed, the declared capacity of

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

an aerodrome, which is the capacity that considers all bottlenecks on the airside and the landside, is often substantially lower than the absolute maximum capacity of the runway system, especially if the runway system is not the most relevant constraining element. For instance, the capacity of Amsterdam *Schiphol* Airport is capped by Dutch law at 500,000 movements per annum (Schiphol Group, 2019). Similarly, at Zurich (ZRH) Airport political considerations limit runway capacity to approximately 70 hourly movements. Berster et al. (2015) suggest that airlines often schedule larger airframes to and from airports which are capacity saturated. Consequently, capacity saturation seems to have a rather direct impact on the average number of passengers per ATM, which in turn should be accordingly treated in a ratio-based modelling approach.

The ratio method appears only to have been applied to define DHLs more generally, such as the DHL for all departing passengers, rather than for specific airport passenger terminal facility sub-sets (e.g. check-in, the security checkpoints or the immigration facility, etc.). This is most probably due to a lack of access to datasets which include detailed passenger flows in and out of terminal facilities. With conventional methods, such as surveys, the systematic collection of passenger flow data in terminal facilities over the course of many years may not be practical. In recent years however, some airport operators have started to collect data from automated passenger tracking systems (PTS) which measure passenger influx in and outflux from facilities as well as the movement of passengers within the terminal. These observations are carried out (i) in a conventional way by utilizing boarding pass readers, turnstiles, light barriers, etc., (ii) by tracking the Bluetooth or Wifi-signal of mobile and portable devices carried by passengers, such as the “SPOPS” system (Hansen et al., 2009), or “SITA iFlow” (Nikoue et al., 2015; Société Internationale de Télécommunications Aéronautiques [SITA],

2013) or (iii) by tracking the movement of passengers with the help of stereoscopic optical sensors and image recognition algorithms (Hänseler, 2020). As a consequence, large datasets describing passenger flows in airport passenger terminals can be and have been accumulated, which demonstrates the potential for these to be used for airport strategic planning applications (Raff & Wicki, 2019).

In the literature there is an emerging body of contributions dealing with the application of PTS data in airport planning. Schultz and Fricke (2011) employed data originating from a video-based PTS to determine a stochastic model of passenger movements in terminals describing tactical decision making and route choice by passengers. Hansen et al. (2009) reported on the application of the SPOPS PTS at Copenhagen Airport, which is used to predict passenger flows and the resulting queue length and congestion levels in terminal facilities in real-time. The SPOPS system is used by the airport operator to manage resources and staffing as well as to provide passengers with detailed information on their expected waiting times at the facilities. Furthermore, Hansen et al. (2009) studied privacy concerns related to Bluetooth-based PTS in airport terminals tracking passenger movements within certain terminal areas for a limited period of time. Nikoue et al. (2015) used [anonymised] Wifi-based tracking data which describes the walking speed of passengers as well as the timing and magnitude of passenger flows obtained with SITA's "iFlow tool". This data was used to model the arrival process at the immigration facility of Sydney International Airport in Australia. Balakrishnan et al. (2016) proposed that by using passenger tracking and localization data, airports might be better capable of monitoring demand and managing staffing in the future. Marzuoli et al. (2018) and Monmousseau et al. (2019) used a combination of mobile phone localization data (call detail records) and social media data (Twitter) to analyse the impact of weather-related disruptions on air transportation and airport operations in particular. Monmousseau et al. (2020) applied the same method to measure the drastic impact of the COVID-19 pandemic on airport operations. Burrieza et al. (2019) used call detail records in combination with airport surveys to characterize airport users (e.g. to distinguish between arriving, departing or transit passengers or to identify visitors and staff, etc.). Finally, in the wake of the COVID-19 pandemic, Hänseler (2020) presented a method for the automatic monitoring of social distancing discipline based on measurement data gathered with the XOVIS passenger tracking system. PTS data has yet to be applied to airport strategic planning contexts more generally, and in particular to the determination of facility-specific DHLs. (pp. 2–4)

2.2 Flexibility in engineering systems

The flexible ASP approaches and frameworks introduced in Section 2.1.1 are based on the idea of "change-resilient" strategic plans, which should provide airport infrastructure with the ability to "adapt to variations in demand and other conditions" (Magalhães et al., 2017, p. 366). The desire to provide flexible and adaptive infrastructure is not an airport-specific phenomenon. Rather, the introduction of flexibilities in strategic plans are of central importance for a whole class of infrastructure known in the literature as *engineering systems*. According to Cardin (2014, p. 2), engineering systems are "complex systems in the aerospace, defence, energy, housing, telecommunication, and transportation industries" which often take up essential functions in our society and have long life cycles of 20 or even more years. Given these long planning horizons, the life cycle performance of engineering systems is significantly affected by uncertainty driven by "environmental, demographic, market, regulatory, and technological forces" (Cardin & Hu, 2016, p. 1). Moreover, investments in engineering systems tend to be *irreversible*: once a system is built, it is usually (at least partially) impossible to recover or salvage the associated investment costs (Dixit & Pindyck, 2012; Trigeorgis, 1996; Van Mieghem, 2003). Investment decisions that have transpired in hindsight to be wrong can therefore only be corrected at a very high cost.

According to the literature, flexible engineering systems are much better at dealing with uncertainty and the irreversibility of investments than conventional engineering systems. In fact, flexible engineering systems are capable of "increas[ing their] expected economic value by providing ... adaptive strategies to respond to uncertainties most profitably" (Cardin et al., 2015, p. 255). Indeed, the literature reports that flexible engineering systems usually result in a 10 % to 30 % higher financial performance over their entire life cycle than conventional, i.e. non-flexible, engineering systems (Cardin, 2014; De Neufville & Scholtes, 2011).

This section deals with the basic concept of flexible engineering systems. Section 2.2.1 provides an overview on how the term *flexibility* is defined in the literature. Section 2.2.2 explains how engineering systems can be made flexible by means of real options, while Section 2.2.3 introduces a number of concepts and frameworks which allow system planners and decision makers to build flexibility into engineering systems.

2.2.1 Definition of flexibility

The literature defines flexibility in engineering systems in a number of different ways. For example, Hu and Cardin (2015, p. 122), with reference to Fricke and Schulz (2005), define a flexible engineering system as a system which is capable of "chang[ing] easily in the face of uncertainty". According to Saleh et al. (2002, p. 4), a flexible system is "able to modify its mode of operation or its attributes", while for Dempsey et al. (1997), flexibility in an engineering system is given by its ability to adjust continuously and constantly. De Neufville (2008, p. 53) points out that flexibility of an engineering system is ensured by the provision and installation of "technical features that enable the owners to change, easily and inexpensively, the configuration of their facility to meet new needs".

The definitions of flexible engineering systems and flexible ASP are much alike. The literature on flexible planning of airports, and airport passenger terminals in particular, is reviewed by Magalhães et al. (2017), who present a number of different interpretations of how scholars define flexibility in the context of ASP. For Kwakkel et al. (2008, p. 22), flexible ASP "is an approach for making plans, particularly for infrastructure developments, that can be easily adjusted over time to the actual situation and conditions". Magalhães et al. (2013, p. 4) define flexibility in airport planning as the "ability to have an infrastructure as mutable as possible to adapt to future needs with minimal investment". Further, for Edwards (2005, p. 85), flexible airport infrastructure is capable of "accomodat[ing to] changes that can rarely be anticipated". In summary, flexible engineering systems, and by analogy flexible airport passenger terminal facilities, provide system designers with options that allow them to exercise flexibility by adapting and adjusting the (airport) system, in order to meet the needs at a future point in time. The actual tools which allow the introduction of flexibility to engineering systems are *real options*, and these are reviewed in the following section.

2.2.2 Real options

The concept of real options is based on options used in finance. As such, an option "represents a right, but not an obligation … to do something at [*sic*] under predefined arrangements" at a future point in time (De Neufville, 2003, p. 7). An option is a contract between a buyer and a seller, which defines the costs of exercising the option in advance. To acquire an option, the buyer pays the seller a *premium*, which is a fee. In finance, two basic types of options exist: *call options* and *put options* (Brealey et al., 2018). A call option constitutes the right, but not obligation, to buy an asset, such as a share, a commodity, etc. at a predefined and fixed *exercise* or *strike price* at a future point in time, even if the current market price is higher. In contrast, a put option represents the right, but not obligation, to sell an asset at a certain strike price. Thus, call options provide the buyer with the possibility to capitalise on opportunities, while put options can act as a form of insurance, which reduce the downside risks of an investment. Consequently, options are tools by means of which the risk of an investment can be managed. Indeed, options have a value that increases with the increasing risk of an investment (Amram & Kulatilaka, 1998; De Neufville, 2003).

Real options differ from options used in finance in such a way as they "deal with physical things rather than financial contracts" (De Neufville, 2003, p. 9). To this end, real options are used to "modify projects" (Brealey et al., 2018, p. 269), since they provide owners and planners of engineering systems with the "right, but not the obligation, to change a system easily in the face of uncertainty" (Cardin, Zhang et al., 2017, p. 228). Real options are the tools that practitioners have at their disposal to make engineering systems flexible (Cardin, 2014; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018). Similar to financial options, real options allow owners to (i) avert the risk of negative developments, and they (ii) provide them with the option to capitalise on opportunities (De Neufville, 2008). For this reason, real options add value to engineering systems (Geltner & De Neufville, 2018; Schwartz & Trigeorgis, 2004).

The literature differentiates between real options *on* systems and real options *in* systems (Cardin & De Neufville, 2009; Wang & De Neufville, 2005), which will be discussed individually in the following sections.

2.2.2.1 Real option *on* systems

Real options *on* systems are a source of managerial flexibility, as they provide system owners with the right, but not obligation, to buy, sell, expand and contract systems (Chambers, 2007; Kincaid et al., 2012). According to Wang and De Neufville (2005), real options *on* systems consider the underlying technical systems as blackboxes. Consequently, practitioners need to have neither in-depth technical knowledge nor a solid understanding of the system in order to be able to properly exercise a real option *on* a system.

Trigeorgis (1996) presents a number of generic real option strategies, some of which are applicable to ASP, while others are more suitable for other fields of application. In the following, a short overview of generic strategies is given. The *option to defer* refers to the right to wait and postpone an investment decision on an engineering system to a future point in time until enough information for well informed decision making is available (Kincaid et al., 2012). This option is especially beneficial for infrastructure projects due to the irreversibility of investments in engineering systems (Chambers, 2007). The *time-to-build option* encourages staged developments in which an investment in an engineering system is divided into a number of sub-projects which are based on each other. This way, instead of deploying the system's entire capacity at once from the start, each future stage is an option which can be realised if required and/or desired. In ASP, the concept of staged developments is well-established, since most airport development programmes are formulated as a series of sequential projects (De Neufville et al., 2013; FAA, 2015; Horonjeff et al., 2010; IATA, 2017). The *option to alter* the operating scale enables flexible adjustments of an engineering system by means of expansion, extension or contraction of the system's capacity or output. This option is ideally suited to ASP, since in this discipline planning should be based on infrastructure that can be flexibly adjusted at a later date (Butters, 2010). The *option to abandon* provides owners with the flexibility to withdraw and sell an engineering system at salvage value[3]. The *option to switch* enables the flexible adjustment of the outputs of a facility according to the current needs of the market. Further, the option to switch may provide planners with the opportunity to produce the same output with different inputs, or to accommodate different customers, markets and missions. The *growth option* constitutes of a current or early investment in future technology, which if successful, enables further growth in the future, e.g. the strategic acquisition of land for future development projects.

2.2.2.2 Real option *in* systems

Real options *in* systems are design features which are deliberately built into a system in order to provide owners, planners and DMs with the flexibility to change and adapt the underlying system. As mentioned by Wang and De Neufville (2005), real options *in*

[3]It should be borne in mind that engineering systems often have a very small salvage value due to the irreversibility of investments (Dixit & Pindyck, 2012).

system aim at changing the system itself. For this reason, decision makers and planners require in-depth technical knowledge of the system in order to be able to design and exercise real options *in* systems efficiently and effectively. In the literature, various examples of real options *in* engineering systems are presented. De Neufville et al. (2006) and Zhao and Tseng (2003) present the case of a multi-storey car park whose foundation is built in such a way that, at a later point in time, additional storeys can be added to the facility. Clearly, investors pay a premium during the initial construction, since the structure is over-designed for the initial stage of the build. However, depending on how the future evolves, owners are provided with the flexibility to substantially increase the capacity of the multi-storey car park. De Weck et al. (2004) discuss the application of real options *in* a system for a communications satellite network which is made flexible by means of staged capacity deployments. Cardin and De Neufville (2009) and Geltner and De Neufville (2018) showcase the application of real options *in* systems for office buildings in the cities of Chicago and Vancouver. These buildings are built in such a way that additional floors can be added at a later date. Chambers (2007) discusses the case of the *25 de Abril Bridge* in Lisbon, Portugal, which, when built in 1962, was structurally designed in such a way that a second deck could be added. Indeed, this real option was exercised in 1999, when the bridge, which initially hosted a 4-lane highway, was retrofitted with additional railroad tracks.

It is worth mentioning that the differentiation between real options *on* systems and real option *in* systems is sometimes quite difficult or even impossible because combinations of real options *in* and *on* systems are often applied. For instance, the "multi-storey car parks case" presented by De Neufville et al. (2006) is based on the combination of a real option *in* a system, i.e. the over-design of the foundation so that parking decks can be added at a later date, as well as the options to defer an investment and a time-to-build option, i.e. staged development.

2.2.2.3 Applications of real options in ASP

A number of airport-related applications of real options have been documented in the literature. One method that is often used by airport planners is *landbanking*. This involves buying strategic land reserves in advance and reserving them for potential future projects (Chambers, 2007). The actual decision to carry out a project on the purchased land can then be deferred to a future point in time. For instance, De Neufville (1991) reports on a successful application of landbanking for a potential replacement airport of Sydney *Kingsford Smith* International Airport in Australia. Magalhães et al. (2013) mention Athens International Airport in Greece, where only half of the airport was built initially and the required land for the other half was secured by means of landbanking. Similarly, Butters (2010) reports on the strategic expansion plan of Dublin Airport in Ireland, which, dependent on future demand levels and traffic mixes, provides for a flexible expansion of terminals and piers. Xiao et al. (2017) introduce an airport capacity planning model which allows the determination of the optimal trade-off between the airport capacity to be built initially versus the size of the landbanking area to be acquired. When the concept of reserving areas and space for future developments is applied within (existing) terminal buildings, it is referred to as *buffer spaces* (Butters, 2010). Within already existing buildings, buffer space can either remain unused until it is finally converted into a complete facility, or buffer space can be made available for interim uses.

Another way of enabling flexibility is to plan *modular airport facilities*; this refers to standardised elements and units which can be built and connected with each other in a repetitive manner (Kincaid et al., 2012; Shuchi et al., 2012). According to Shuchi (2016), a modular terminal design allows for the construction of airport terminal facilities which are expandable, flexible, cost-effective and can be rapidly built. Modular buildings and facilities have already been used in ASP. For instance, the terminal of Southampton Airport in the UK is built in such a modular way which "facilitates future expansions that could be easily achieved without disruptions on the existing operations" (Shuchi et al., 2012, p. 6).

According to Shuchi et al. (2012) and Shuchi (2016), *connected buildings* and *temporary facilities* are further measures to enable flexibility. In connected terminals, operations can be moved from one area of the building to another without major disruptions to airport and passenger processes. Furthermore, connected buildings, as they are, for instance, to be found at Amsterdam *Schiphol* Airport, San Francisco International Airport and Singapore *Changi* International Airport, allow facility expansions without the introduction of split operations, i.e. the fragmentation of services and processes between different buildings, which could lead to a deterioration of the service quality perceived by customers (Shuchi et al., 2012; Shuchi, 2016). Temporary facilities are infrastructure that is purposely made available for limited periods of time. They are often based on simple constructions or, as described by Shuchi (2016), are inflatable building structures. Temporary facilities can be particularly advantageous for airports that are exposed to high demand uncertainty (De Neufville et al., 2013; Shuchi, 2016). This is for instance the case for aerodromes where low-cost airlines comprise a large part of the traffic (De Neufville, 2008). Practical applications of temporary airport buildings based on simple structures can be found at Berlin *Schönefeld* Airport, Amsterdam *Schiphol* Airport or Malta International Airport (Neptunus Structures [Neptunus], 2021). Similarly, the airports of Boston and Los Angeles make use of inflatable buildings as a temporary means of providing additional passenger terminal and maintenance facilities (Shuchi, 2016).

Finally, *shared-use*, *mixed-use* or *common-use facilities* are also often used to introduce flexibility in airport passenger terminals. Shared-use and mixed use facilities can be accessed by various users, e.g. airlines, aircraft types, passenger types and used for a number of different functions, e.g. for arrivals and departures, or international and domestic passengers (De Neufville & Belin, 2002). For instance, flexible gate lounges, also known as *swing gates*, are equipped with movable walls that allow airport operators to make facilities accessible for different types of passengers, such as international or domestic passengers (De Neufville, 2008; Shuchi et al., 2012). Shared-use facilities allow airports to adjust and manage the capacity of airport infrastructure both in the short-term as well as in the long-term at relatively low costs. According to Kincaid et al. (2012) and Landrum & Brown et al. (2010), shared-use facilities have already being used at various airports, such as Vancouver International Airport, Dallas Fort Worth International Airport and Denver International Airport.

Common-use terminal equipment (CUTE) and *common-use self-service (CUSS)* are standardised information technology (IT)-systems and equipment which can be used by a number of different users. These infrastructure types allow airports to avoid the use of facilities only by individual airports or handling agents, but to make the facility available to all stakeholders simultaneously. Airport Council International (ACI, 2020a) recommends that airports use common-use equipment whenever possible, as this can reduce infrastructure requirements. Indeed, the potential capacity gains given by the flexibility of common-user systems can be significant. For instance, at Geneva Airport in Switzerland, the introduction of common-use systems improved the effectiveness of the check-in facility by about 25 % (Chambers, 2007).

2.2.3 Enabling flexibility in engineering systems

Various approaches are presented in the literature that enable planners and decision makers to develop, evaluate and plan flexible engineering systems. This section discusses the most important contributions to the literature on this topic.

Cardin (2014, p. 1) proposes a "taxonomy of systematic procedures" based on five phases, which aims to enable flexibility for engineering systems. First, planners determine a so-called standard or *baseline* design, which is a conventional, i.e. inflexible, design of an engineering system. At later stages of the process, the baseline design is used to evaluate and benchmark flexible design configurations. In a second step, known as *uncertainty recognition*, drivers of uncertainty are identified and described appropriately (see Section 2.3). Given a baseline design and a description of uncertainty, planners then focus on the *concept generation* in a third step. At this stage, planners create so-called *candidate flexibilities*, which are flexible system designs based on real options *in* system and/or real options *on* systems. With a number of candidate flexibilities at hand, DM perform a *design space exploration* in a fourth step, usually in comparison with the baseline, in which "the most valuable [flexible] systems design concepts and decision rules to operate the system" are determined (Cardin, 2014, p. 17). Methods that can be used for the evaluation of candidate flexibilities and subsequent selection of the most appropriate system design are presented in Section 2.4. The last step of Cardin's taxonomy is *process management*, which aims at providing the conditions which are required to successfully generate flexibilities and also facilitating, i.e. safeguarding, an environment in which flexible design concepts can be implemented and exercised at later points in time. In this way, owners and planners ensure that design flexibilities remain available in the future.

In addition to the methodology of Cardin (2014), the literature contains a number of other relevant contributions on approaches that enable flexibility in engineering systems. De Neufville and Scholtes (2011) suggest a method similar to the one presented by Cardin (2014), which, however, consists only of four distinct phases: (i) *estimating the distribution of future possibilities*, in which sources of uncertainty are identified and described appropriately; (ii) *identifying candidate flexibilities*, which deals with the determination of flexible system designs; (iii) *evaluating and choosing flexible designs*, which deals with the evaluation of designs and the selection of the best design; and (iv) *implementing flexibility*, which ensures that design flexibilities remain available in the future. Hu and Cardin (2015) propose a methodology which is also based on four phases: (i) *initial design*, (ii) *dependency and uncertainty analysis*, (iii) *flexible design opportunities identification* and (iv) *flexibility valuation*. Finally, De Neufville (2008) and De Neufville et al. (2006) both mention and apply a three-phased process for the implementation of flexibility in systems engineering which consists of (i) the recognition of the range of uncertainty, (ii) the definition of flexible design opportunities and (iii) the analysis of design opportunities.

Although some of the approaches mentioned above come with a differing number of phases, different names for the phases, or assignments of activities to phases[4], all these approaches share the same goal; they intend to establish flexibilities in engineering systems. For this purpose, all the approaches mentioned in the literature suggest a similar course of action, which can be summarised as follows: (i) recognition and modelling of uncertainty, (ii) identification of candidate flexibilities, and (iii) evaluation and selection of candidate flexibilities. The recognition and modelling of uncertainty as well as the evaluation and selection of candidate flexibilities will be discussed further in Sections 2.3 and 2.4, while candidate flexibilities and real options applied in the context of ASP have already been discussed in Section 2.2.2.

2.3 Recognition and modelling of uncertainty

Because the life cycles of engineering systems are extremely long, the performance of these facilities is significantly influenced by uncertainty (Cardin, 2014; Cardin et al., 2007; De Neufville & Scholtes, 2011; De Weck et al., 2004; Eckert et al., 2009; Mikaelian et al., 2011; Nilchiani & Hastings, 2007). Consequently, owners and planners of engineering systems are best advised to acknowledge "the fundamental reality that [they] cannot predict the future precisely" (De Neufville & Scholtes, 2011, p. 34). This section provides a definition of the term *uncertainty* as well as an overview of how drivers of uncertainty for engineering systems can be identified and classified. Furthermore, drivers of uncertainty affecting ASP in general, and ASP of airport passenger terminals in particular, are discussed in more detail. This section concludes with an overview of the methods which allow mathematical modelling and the description of uncertainty.

[4]For instance, Cardin (2014) explicitly deals with the generation of a baseline design in the first phase, while De Neufville and Scholtes (2011) integrate the baseline generation in the third phase *evaluating and choosing flexible designs*. Or, as another example, the approaches presented by De Neufville (2008), De Neufville et al. (2006) and Hu and Cardin (2015) do not explicitly cover the step *process management* as proposed by Cardin (2014).

2.3.1 Definition of uncertainty

Uncertainty can be generally defined as "any departure from the unachievable ideal of complete determinism" (Walker et al., 2003, p. 4). In this context, a distinction can be made between different types of uncertainty: *known uncertainty*, *unknown uncertainty*, *uncertainty in the data* and *uncertainty in the description* (De Weck et al., 2007; Hastings & McManus, 2005). Known uncertainty refers to data or information which is measurable or observable, while the opposite is true for unknown uncertainty. Uncertainty in the data refers to missing, inaccurate, wrong or inconsistent measurements and observations. Uncertainty in the description refers to uncertainty which arises due to incomplete or unclear definitions. In this study, the focus is on *known* sources of uncertainty as only these can be described by means of historical observation and knowledge.

2.3.2 Recognition of uncertainty

ASP is subject to a large number of different sources of *known uncertainty*, which can either be classified as *endogenous uncertainty* or *exogenous uncertainty* (De Weck et al., 2007; Halpern, 2017). Endogenous uncertainty has its origin within a system, such as an airport, while exogenous uncertainty originates from outside of a system.

2.3.2.1 Endogenous uncertainty

According to De Weck et al. (2007), uncertainty from (i) a *product context* and (ii) from a *corporate context* is endogenous. Uncertainty from a product context arises for instance due to technological risks, reliability of a product or technology, as well as unconsidered interaction between different technologies and/or products. Uncertainty from a product context is well covered in the literature on airport planning and operation. Kincaid et al. (2012, p. 14) point out that "developments in aircraft technology, air traffic control, and passenger facilitation can have implications for traffic levels and airport capacity". For instance, De Barros and Wirasinghe (1998) and Lim (2008) examined how an airport passenger terminal's capacity is affected by the introduction of very large aircraft, such as the Airbus A380. Further, the impact of technical and procedural improvements in the aircraft turnaround process may affect airport passenger terminal facilities (Schmidt, 2017). Another source of uncertainty is future developments in the area of IT, which are expected to have a major impact on the degree of automation of airport processes (Ashford et al., 2011). For instance, so-called *self-service processes* in use at check-in, immigration or emigration facilities affect the required capacity levels (Castillo-Manzano & López-Valpuesta, 2013; Shuchi et al., 2012). According to Kalakou et al. (2015, p. 203), a number of key IT technologies such as "identity management and biometrics, near field communications, big data analytics and smartphone applications" promise capacity gains. Additionally, uncertainty originates from what customers may expect from an airport passenger terminal in the future. On this issue, Landrum & Brown et al. (2010, p. 76) mention potential future trends in the area of concessions and "food and beverage trends", which would ultimately require airport operators to fundamentally adapt the design of passenger terminal buildings.

Uncertainty in a corporate context includes unforeseen changes of contractual agreements or changes of the corporate strategy. For instance, Burghouwt (2007, p. 188), with reference to Genus (1995), explains that "airport management may have vague or non-specified strategies, goals and objectives at the beginning and during the planning process", which may lead to increased levels of uncertainty for ASP. As an example, the privatisation of airports as well as mergers and acquisitions can affect ASP projects in a significant way (Burghouwt, 2007; Kwakkel et al., 2010). Additionally, Butters (2010) and IATA (2017) mention that the environment in which an airport operates can be a major source of uncertainty. For example, the allocation and availability of resources, e.g. staffing, maintenance activities, cleaning, etc., can affect the operational efficiency and efficacy of an airport in a substantial way (IATA, 2017).

2.3.2.2 Exogenous uncertainty

Exogenous uncertainty originates from outside of a company or organisation, namely from (i) a market context, (ii) a political and cultural context or (iii) a use context (De Weck et al., 2007). Uncertainty in the market context most prominently originates from an under-estimation or an over-estimation of demand as well as errors in the actual forecasting methods. Besides that, airports are subject to uncertainty due to competition with other airports, customers decisions, such as an airline's decision to launch or withdraw services, as well as volatilities in revenues, costs and the economy in general. Demand uncertainty manifests itself in the overall volume of traffic, the traffic mix and the peaking characteristics of traffic. According to Kincaid et al. (2012) and Kwakkel et al. (2010), the aggregated volume of traffic, expressed in the total number of passengers per annum, total number of ATM, air cargo volumes, etc., is both volatile over time and susceptible to trend breakers, such as the 9/11 terrorist attacks. Indeed, historic evidence shows that with increasing volatility of demand, the ability of airport planners to create a consistent demand outlook is reduced significantly (Burghouwt, 2007; De Neufville & Barber, 1991).

Besides the absolute volume of demand, it is also the mix and type of traffic, which poses a major source of uncertainty. The mix and type of traffic describes what the traffic comprises, such as "domestic versus international, origin/destination (O/D) versus connecting, low cost carrier (LCC) versus full service/legacy carrier, turboprop versus regional jet versus large jets, and so forth" (Kincaid et al., 2012, p. 14). It is well known that the mix and type of traffic strongly depends on the business and network decisions of the airlines frequenting an airport. For instance, LCCs are known for "routinely experiment[ing] with alternative, non-traditional destinations" (De Neufville, 2008, p. 52), which makes secondary airports often rather dependent on traffic generated by LCCs (Chambers, 2007; Jimenez et al., 2017). Again, a network airline might decide to promote an O/D airport to a hub (or vice versa), which ultimately has an impact on the demand patterns, and thus requires airports to adjust their infrastructure (IATA, 2017;

Landrum & Brown et al., 2010). For passenger terminal facilities in particular, changes in the traffic mix and type can substantially influence the capacity needed to meet demand. Thus, a change in the ratio between domestic and international passengers affects passenger flows through the immigration and emigration facilities, which ultimately defines their required capacities.

The timing and magnitude of traffic peaks are subject to uncertainty as well (Burghouwt, 2007; De Neufville & Belin, 2002). While large airports and mature hubs tend to be capacity saturated (see Section 2.1.4), and therefore less prone to peaking-related uncertainty, smaller airports are often strongly affected by even small changes in the peaking pattern (Chambers, 2007). At large airports which already handle a lot of traffic, the addition of a single flight scheduled to operate during the peak period has a less significant impact on traffic flows during this time interval than is the case at a small airport, where an additional flight affects the total peak load in a more pronounced way. A further point is that airports are in competition with each other, which poses another source of uncertainty (IATA, 2017). This is especially true for so-called *multi airport systems*, where multiple airports share large parts of their catchment area (De Neufville et al., 2013). Finally, uncertainty in the behaviour of passengers may have an influence on facility requirements as well. For instance, the average number of pieces of baggage carried per passenger, which affects the design and sizing of check-in facilities and baggage handling system (BHS)s, is subject to uncertainty. It has been found that the number of pieces of baggage carried per passenger "tends to vary by world region based on cultural factors", and has significantly decreased over recent years "due to additional security requirements as well as fees on checked baggage" (IATA, 2017, p. 34).

Global, regional or local economic conditions and economic cycles can lead to uncertainty (Burghouwt, 2007; Kincaid et al., 2012; Magalhães et al., 2013). In the past, it has been shown that during periods of economic growth air traffic tends to grow faster than the economy, while it decreases more rapidly in times of economic downturn (Kincaid et al., 2012). Airports "that serve communities whose economy is dominated by one particular industrial activity, or by a single company's business activities" are particularly vulnerable to the general state of the economy (Landrum & Brown et al., 2010, p. 22). Moreover, the deregulation of the aviation market led to increased demand volatility (De Neufville & Barber, 1991), since, according to De Neufville et al. (2013, p. 94) "barriers to changes in prices, frequency in services, and routes [were removed]". Kwakkel et al. (2010) expect both the dynamics and the volatility of the market to increase even more in the future thanks to global efforts to liberalise the market, for instance through open sky treaties. Finally, uncertainty in general market conditions may affect energy prices (De Neufville, 2008; IATA, 2017) or the cost of capital (Burghouwt, 2007; Magalhães et al., 2013) and construction (De Neufville et al., 2013; Flyvbjerg et al., 2003; Knudsen, 1977), which, in turn, can strongly impact airports and their strategic plans.

2.3.3 Modelling of uncertainty

In an ASP project not all sources of uncertainty can be taken into account for a number of reasons. For one thing, there are too many potential sources of uncertainty, and for another, not all sources of uncertainty are of equal importance. Therefore, planners need to focus on the sources of uncertainty that they feel will most affect the planning success of an ASP project. Once these sources of uncertainty have been identified and selected for further consideration, planners need to outline them with appropriate mathematical models. For this purpose, the literature presents a number of different methods to model uncertainty, which are categorised by Cardin (2014) and De Weck et al. (2007) as either *formal approaches* or as *practical procedures*.

2.3.3.1 Formal approaches

According to De Weck et al. (2007), formal approaches are based on the application of: (i) probability theory, such as by expressing the relative likelihood of occurrence of events or outcomes, (ii) Bayesian probability, such as by expressing probabilities based on *Bayes' theorem*, which allows one to reassess the plausibility of a statement in the light of new information, (iii) possibility theory, such as fuzzy logic (Zadeh, 1978), or (iv) *Dempster-Shafer theory*; this is "based on belief functions and plausible reasoning, which is used to combine separate pieces of information (evidence) to calculate the probability of an event" (De Weck et al., 2007, p. 7). The first three approaches can be used if planners have a solid understanding and knowledge of the drivers of the uncertainty they aim to model. Therefore, planners require well-founded information on the (joint) probability distributions of the drivers of uncertainty in order to apply one of these methods. In practical planning applications, probability theory, Bayesian probability and possibility theory are regularly applied in order to determine inputs for models, such as starting conditions or parameters. In contrast, Dempster-Shafer belief functions (Dempster et al., 1967; Shafer, 1976) are less frequently applied in the domain of ASP. However, it should be emphasised here that, unlike other formal approaches, which are heavily reliant on the availability of input data, Dempster-Shafer belief functions are to be favoured for applications where no or only limited information on the sources of uncertainty is available.

2.3.3.2 Practical procedures

Practical procedures can be divided into two distinct subgroups according to whether a source of uncertainty is modelled with continuous real-valued variables or by means of discrete events. Continuous real-valued approaches describe the parameter(s) of uncertainty with real-valued random variables (De Weck et al., 2007). To this end, both *diffusion models* and *lattice models* find application in the literature (Cardin, 2014).

Diffusion models. Diffusion models are solutions of stochastic differential equations in which at least one term is a stochastic process. Stochastic differential equations are widely used to model time-dependent processes which are subject to both deterministic trends, also called drifts, as well as stochastic influences. In the literature on engineering systems, *geometric Brownian motion (GBM)* is the most popular diffusion model used to describe sources of uncertainty (De Weck et al., 2007). According to Alexander (2008) and Seydel (2006), a GBM is defined as any solution of the following stochastic differential equation

$$\frac{dX_t}{X_t} = \mu dt + \sigma dW_t \tag{2.3}$$

where X_t describes the state of a property, such as the demand of an airport at time t. μ is the percentage drift rate, which is a parameter describing the constant deterministic growth rate of the property X, while σ is a parameter quantifying the constant percentage volatility of X. Finally, W_t is a *Wiener process*, which is also called *Brownian motion*. As such, a Wiener process is a stochastic process which has the following properties: (i) W_0, which is W_t at $t = 0$, is defined as $W_0 \equiv 0$, (ii) the increments of W_t are normally distributed with a mean of zero and a variance of $t_2 - t_1$: $W_{t_2} - W_{t_1} \sim \mathcal{N}(0, t_2 - t_1)$, given points in time $t_2 > t_1$, (iii) all increments of the process over non-overlapping time intervals are independent and (iv) W_t is a continuous process (Gubner, 2006; Seydel, 2006). According to Ross (2014), Equation 2.3 mentioned above has the following analytical solution for an arbitrary initial value X_0:

$$X_t = X_0 \cdot \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t\right). \tag{2.4}$$

As can be inferred from Equation 2.4, the logarithm of the ratio between X_t and X_0 follows a term which consists of two parts: (i) a deterministic part which is characterised by the percentage drift μ and (ii) a stochastic part which represents random changes in the process by means of Brownian motion. Thus, X_t is a random variable which follows a log-normal distribution.

In order to model a variable subject to uncertainty by means of GBM, both the mean percentage drift μ and the volatility σ must be estimated accordingly. De Weck et al. (2007) and Mun (2002) propose the estimation of the average percentage drift μ by means of the average observed relative change of X, and the volatility σ with the observed standard deviation of the relative change of the variable of interest. With a parametrised GBM, planners can now create so-called *paths*, also known as *scenarios*, that describe possible future evolutions of the uncertain variable over a certain period of time. Because GBM is based on a random process, there are an infinite number of such paths. Therefore, for practical applications, planners usually sample, i.e. generate realisations of the random process by means of *Monte Carlo simulation*, a large but finite number of paths (De Weck et al., 2007). In order to cover as many of the potential future developments as possible, the literature recommends the creation of between 2000 and 10 000 individual scenarios (Cardin et al., 2015; Cardin, Xie et al., 2017; De Neufville et al., 2006; Geltner & De Neufville, 2018; Hu et al., 2018; Hu et al., 2020; Hu & Guo, 2019).

Most probably, the best known application of GBM is in the *Black-Scholes model* (Black & Scholes, 1973), which is a model for the valuation of (European-style) financial options. Besides that, GBM is used in numerous applications in order to model stock prices (Reddy & Clinton, 2016), the price of natural resources, such as for wood (Thorsen, 1999), future cash flows of an airport (Pereira et al., 2006), electric power consumption (Marathe & Ryan, 2005), etc. In the literature focusing on the applications of real options in engineering systems, GBM is considered by some authors as "the conventional way" to model uncertainty (Cardin et al., 2015, p. 257). Indeed, GBM is widely used in flexible engineering systems applications, where it is used to model demand (Cardin & Hu, 2016; Cardin, Xie et al., 2017; De Neufville et al., 2006; Hu & Cardin, 2015; Hu et al., 2018; Jin et al., 2011; Suh et al., 2007; Zhang, 2016; Zhao et al., 2018), disposal costs (Hu et al., 2018), or the price of real estate (Geltner & De Neufville, 2018).

Even though the application of GBM to model factors subject to uncertainty is appraised by the literature, the method comes with deficiencies that are worth mentioning. First, it is assumed that the percentage drift μ and the percentage variability σ are constant properties, which, as illustrated by Marathe and Ryan (2005), is an assumption which does not always hold under real-world conditions. Second, GBM assumes continuity in time, meaning that jumps or discontinuities from one state to another cannot be modelled. For this reason, planners must be sure that the processes they model by means of GBM are continuous. Because GBM represents the growth of a variable X by means of a log-normal growth process, extremely rare events, such as a market crash, are under-represented or even missing altogether. The log-normal distribution underlying GBM is not skewed, which means that it is symmetric about the mean. Consequently, it is assumed, for example, that extreme positive and negative growth rates have the same probability, but this is often not the case in practical applications. And finally, diffusion models require a large number of samples to be drawn, which can lead to greater complexity (Cardin, 2014).

Lattice models. In lattice models, time is considered a discrete quantity. Thus, in contrast to diffusion models, a quantity X is not represented continuously, but the state of X is described exclusively for a discrete number of points in time. Lattice models are based on a tree-like structure, i.e. starting from a predefined initial state X_0 in time period $t = 0$, a tree describing the evolution of possible states of X over time t is constructed. From each time period to the next, the state of X can thereby only change according to a number of previously defined paths, all of which have a given probability of occurrence. For instance, as illustrated in Figure 2.1, in a *binomial lattice model*, the state of X_t can only evolve to X_{t+1} according to two distinct paths, known as u (*up*) and d (*down*), which occur with probabilities p and $1-p$, respectively[5].

According to Chambers (2007), a binomial lattice model is statistically equivalent to a GBM for $\Delta t \to 0$ and $t \to \infty$ if the following conditions apply for the up-movement u, down-movement d and probability p:

$$\begin{aligned} u &= \exp(\sigma\sqrt{\Delta t}) \\ d &= \frac{1}{u} \\ p &= \frac{1}{2} + \frac{\mu\sqrt{\Delta t}}{2\sigma}. \end{aligned} \tag{2.5}$$

[5]Besides binomial lattices, the literature also mentions *trinomial* and *multinomial lattice models*. In a trinomial lattice, the state of X might evolve through 3 paths with assigned probabilities of occurrence, while in a multinomial lattice, more than 3 paths are available. As a consequence, however, as the number of possible paths increases, the complexity of the tree increases accordingly.

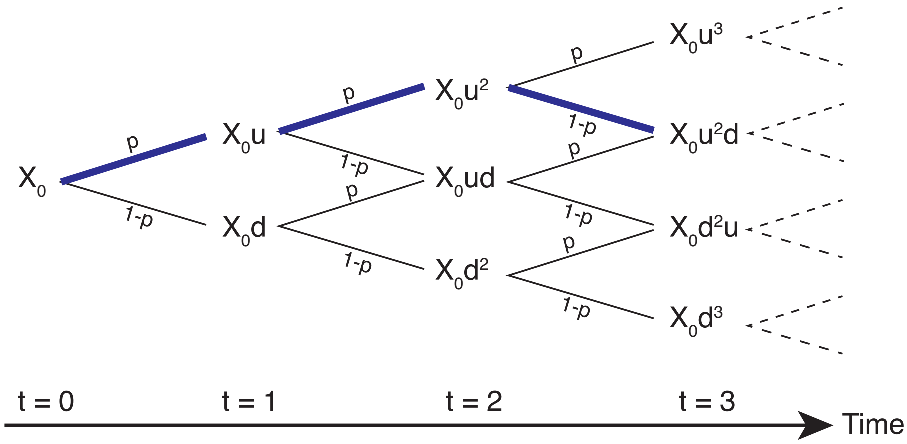

Figure 2.1: Example of recombining binomial tree. One sample path is indicated in blue.

The lattice depicted in Figure 2.1 is *recombining*, where at each node the up and down movements are symmetrical in magnitude but different in sign. This yields trees where, for instance at time period $t = 2$, the middle mode is identical for the up bifurcation of X_0d in $t = 1$ and the down bifurcation of X_0u in $t = 1$. Consequently, the number of nodes in the tree and the number of paths to the same outcome are significantly reduced. In contrast, if a downward movement following an upward movement does not lead to the same state of X as when the process is carried out in the opposite direction, the resulting tree is called a *non-recombining* tree. Non-recombining trees, however, become very complicated (or *bushy*) with an increasing number of periods t.

In order to know which states the variable X can reach at which points in time or via which paths these states can be reached, the entire tree must be determined. This process can be very time-consuming and computationally intensive, especially when many points in time and/or complex tree structures are considered. Therefore, it is advisable to limit the number of periods in a lattice model. For instance, De Weck et al. (2007) point out that for a small tree, e.g. 5 time periods, lattice models prove to be computationally more efficient than GBMs, while Kwok (2008) mentions that the opposite is true for large trees, where GBM can lead to better results in less computational time. Another disadvantage of lattice models is the fact that the simultaneous modelling of several variables is extremely limited (Cardin, 2014). For this reason, Mun (2002) explains that lattice models are better suited for problems where only one single source of uncertainty is considered, while GBM is better capable of handling several sources of uncertainty.

Lattice models find wide application in the evaluation of (real) options, see Section 2.4. To model uncertainty for engineering system-based applications, however, lattice models are not used as often as GBM. Nevertheless, Chambers (2007) uses a binomial tree to model uncertainty in airport demand, Chaize (2003) and De Weck et al. (2004) model uncertain demand for communication satellites, Moel and Tufano (1999) model uncertainty in copper prices and Khansa and Liginlal (2009) model uncertainty in cash flow.

Discrete events. To model discrete events which are subject to uncertainty, such as earthquakes, changes in policies or regulations, severe weather events, etc., the application of either decision trees or scenario planning is recommended by the literature (Cardin, 2014; De Neufville, 1990; De Weck et al., 2007). A decision tree is a conceptual device based on an enumeration which describes how an uncertain variable can evolve over a number of decision nodes (similar to the nodes of the tree). At each decision node, the uncertain variable can change its value or state based on a set of probable alternatives or possible outcomes (De Neufville, 1990; Hansson & Hadorn, 2016). For instance, Chambers (2007) presents a decision tree to model demand for an airport when considering the uncertainty of market entries of low cost carriers. Scenario planning, also known as the *Delphi method* (Helmer, 1967), is based on the generation of a limited number of scenarios by means of expert knowledge and opinion. These scenarios are defined in such a way that they capture the entire range of "future worlds that might occur" (De Weck et al., 2007, p. 10). Unlike most methods presented above, scenario planning does not require large sets of input data, but rather relies on expert knowledge. However, the definition of a scenario is usually a complex, complicated and lengthy task, which binds substantial personal resources (Cardin, 2014). In the literature on flexible engineering systems, scenario planning is infrequently mentioned. An example is provided by Silver and De Weck

(2007), who describe uncertain future demand for heavy lift launch vehicles for space exploration by means of scenario planning.

2.4 Evaluation and selection of facility requirements

Given both the candidate flexibilities for an engineering system as well as the factors of uncertainty that have been identified and modelled by means of the methods presented in Section 2.3, airport planners and DMs must determine which system design, i.e. which candidate flexibility, is most beneficial. In Section 2.2.3, planners are advised to compare the performance of all candidate flexibilities with the performance of an inflexible baseline design. This allows DMs to select the candidate flexibility that achieves the best performance. This candidate flexibility is the one that should then be implemented.

In Section 2.4.1, methods are presented that can be used to quantitatively and objectively describe the economic performance of candidate flexibilities. Such a valuation method can be used to compare candidate flexibilities with the performance of the inflexible baseline design. Cost and revenue functions applied in the valuation model are reviewed in Section 2.4.2. Furthermore, an economic evaluation model serves as the foundation for both conventional and flexible CEP models, which are used in turn to create optimal facility requirements for airport passenger terminal facilities. Conventional CEP models are reviewed in Section 2.4.3, while Section 2.4.4 is dedicated to flexible CEP models.

2.4.1 Economic evaluation of facility requirements

To evaluate the *quality* of candidate flexibilities or facility requirements, DMs must be capable of "estimating how much [a certain] choice [,i.e. a facility requirement or candidate flexibility,] may be worth" (De Neufville, 1990, p. 198). By conducting a ranking of all evaluated choices "by some index of merit" and finally selecting the option which performs best, the *optimal* facility requirement is selected accordingly (De Neufville, 1990,

p. 198). The literature, as reviewed by Remer and Nieto (1995a, 1995b), presents various indices of merit that can be used to evaluate facility requirements from an economic perspective. As such, the indices can be assigned to 5 different groups: (i) net present value methods, (ii) rate of return methods, (iii) ratio method, (iv) payback methods and (v) accounting methods.

2.4.1.1 Net present value methods

The net present value (NPV)-method, often also referred to as the discounted cash flow (DCF)-method, is based on the assumption that the economic performance of a system, a facility, an asset, a project, etc. can be assessed with the discounted sum of all future cash flows. Cash flows can be either costs $\mathcal{C}_t$ or revenues $\mathcal{R}_t$ which are incurred at certain points in time t. Because the NPV method compares cash flows that occur at different points in time, the so-called *time value of money* must be taken into account in each case. The time value of money quantifies the opportunity costs of spending money rather than either saving it or investing it in some (more profitable) ways. As explained by De Neufville (1990, p. 204), "a dollar now and a dollar later are not the same". Indeed, future money is usually worth less, since (i) a "dollar today can be invested to start earning interest immediately" (Brealey et al., 2018, p. 14), and (ii) "future money might not materialize in full or at all, since the future is uncertain" (Geltner & De Neufville, 2018, p. 2). Consequently, cash flows occurring at different points in time can only be compared with each other once they have been *discounted*, which means that they have to be brought to a common point in time. For this reason, DMs and planners often determine the *present value* of future cash flows. For this purpose, the present value $PV(\cdot)$ of a revenue $\mathcal{R}_t$ or cost $\mathcal{C}_t$ occurring at point in time t is calculated with these compound amount formulae[6]

$$PV(\mathcal{R}_t) = \frac{\mathcal{R}_t}{(1+\delta)^t} \qquad PV(\mathcal{C}_t) = \frac{\mathcal{C}_t}{(1+\delta)^t} \tag{2.6}$$

[6]The compound amount formula is used to calculate the present value of a cash flow which occurs after t periods. To calculate the present value in a continuous way, the continuous amount formula, which is defined as $PV(\mathcal{R}_t) = \mathcal{R}_t \exp(-\delta t)$ and $PV(\mathcal{C}_t) = \mathcal{C}_t \exp(-\delta t)$, can be applied accordingly.

where $0 \leq \delta \leq 1$ is the *discount rate*, which "represents the way money now is worth more than money later" (De Neufville, 1990, p. 205). As such, the discount rate δ "account[s] for time and risk", i.e. the opportunity costs of future cash flows (Geltner & De Neufville, 2018, p. 2). The discount rate is a pivotal parameter which significantly affects the resulting present values (De Neufville, 1990). To illustrate matters, the earlier (from the present day) a cash flow occurs and the lower the discount rate, the higher is the resulting present value, while the opposite is true for high values of δ and/or cash flows emerging in the far future (De Neufville & Scholtes, 2011). Consequently, the selection of a reasonable and realistic discount factor is not a trivial matter, but rather a topic of ongoing investigations and discussions in the literature (Brealey et al., 2018).

The discount rate is the rate of return applied to adjust future cash flows to their present value. As such, the discount rate should always be equal or greater than the internal cost of capital of a company (De Neufville, 1990). For the choice of an appropriate discount rate, many authors therefore recommend using the weighted average cost of capital (WACC) after taxation, which "represents the average cost return expected by the owners and banks that finance a project" (De Neufville & Scholtes, 2011, p. 201). Other scholars recommend defining the discount rate based on the sum of the risk free rate and a risk premium (Geltner & De Neufville, 2018). With this method the risk free rate specifies the interest rate, and thus the return that an investment with zero risk, such as a government issued bond, yields. The risk premium, on the other hand, quantifies "what the market 'offers' to investors as the amount of extra expected return … that compensates investors for taking on the risk associated with the given investment" (Geltner & De Neufville, 2018, p. 18). For many practical applications, however, planners cannot choose a discount rate at all, but rather have to apply a value which is imposed by a competent authority or the management. Therefore, there is no such thing as a universally applicable discount rate, but rather the choice of an appropriate value is company-specific. Nevertheless, there are certain general tendencies: De Neufville (1990, p. 230) points out that discount rates are usually "lower in industries regulated by the government than for companies that are not", since activities involving the government are usually subject to less risk than this is the case in solely industry-driven undertakings. Here, De Neufville states that companies in the private sector typically apply discount rates in the range of 10 % to 15 %, while the discount rate for state-regulated companies is often less than 10 %. However, these figures appear to be rather high for the current market conditions in which the risk-free rate is substantially lower than it used to be 30 years ago (Organisation for Economic Co-operation and Development [OECD], 2021).

Under the assumption that (i) the discount rate δ is known and constant over the entire planning horizon T for which an engineering system shall be evaluated, and (ii) future costs and revenues can be forecasted for all planning phases $t = 1, 2, \ldots, T$ considered, the *net present value* NPV of a project, an asset, a system, etc., is defined as

$$NPV = -\mathcal{C}_0 + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} (\mathcal{R}_t - \mathcal{C}_t) \tag{2.7}$$

where $\mathcal{C}_0$ specifies the initial costs of a project occurring at $t = 0$. Equation 2.7 can thus be applied to calculate the NPV of an airport passenger terminal facility i. It is assumed that for facility i both the future operational capacity $\mathbf{K}_i = [K_{i,1}, K_{i,2}, \ldots, K_{i,T}]$ as well as the expected DHL demand levels $\mathbf{d}_i = [d_{i,1}, d_{i,2}, \ldots, d_{i,T}]$ are known for all planning phases $t = 1, 2, \ldots, T$ considered in an ASP project. Consequently, the NPV is defined as

$$NPV(\mathbf{K}_i, \mathbf{d}_i) = -C_0 + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} (\mathcal{R}_{i,t}(d_{i,t}, K_{i,t}) - \mathcal{C}_{i,t}(d_{i,t}, K_{i,t})) \tag{2.8}$$

where revenues $\mathcal{R}_{i,t}(d_{i,t}, K_{i,t})$ and costs $\mathcal{C}_{i,t}(d_{i,t}, K_{i,t})$ are assumed to be a function of DHL demand $d_{i,t}$ and operational capacity $K_{i,t}$ in planning period t.

In the valuation of projects using the DCF-method, DMs are advised to accept projects with a positive NPV and reject those which result in negative NPVs, since projects with a positive NPV add value to a company. If there are more than one project alternative with positive NPVs to choose from, DMs should select the variant that comes with the highest

NPV.

Because of its universal applicability, certain scholars see the DCF-method as the "workhorse" of infrastructure project evaluation methods (Geltner & De Neufville, 2018, p. 2). This explains why the DCF-method is widely used for the evaluation of infrastructure and real estate projects in general (De Neufville, 1990; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018). Besides this, the method is also applied in other areas, such as in the chemical engineering industry (Garrett, 2012), for the planning of railway and highway infrastructure (Milenković et al., 2016; Rogers & Enright, 2016), electricity supply infrastructure (Khatib, 2003), etc. For airport-related applications, the DCF-method also finds widespread acceptance, such as for example to analyse refurbishment options for airport passenger terminals (Parker et al., 2011), to evaluate airport security infrastructure (Stewart & Mueller, 2014) or to evaluate the re-utilisation of airports (Nikoloudis et al., 2017).

2.4.1.2 Rate of return methods

Rate of return methods calculate the discount rate required for a project to achieve a NPV of zero. Rates of return can therefore be regarded as benchmarks: if the rate of return achieved by a project is higher than the cost of capital of a company, an investment is profitable. For airport-related infrastructure projects, rate of return methods have been applied for instance for the determination of (fair) return rates for shareholders of airports (Carney & Mew, 2003; Chaudhuri et al., 2015), the evaluation of airport capacity options (Irvine et al., 2015) or for airport parking facilities (Javid & Seneviratne, 2000).

2.4.1.3 Ratio methods

Ratio methods evaluate a project by comparing two measures with each other. The *cost-benefit ratio* method, which compares the costs of a project with the expected benefits, is most popular. While experience shows that capturing costs is straightforward, quantifying the benefits can sometimes be complicated (Remer & Nieto, 1995b). In the United

States, airport infrastructure projects which are funded through the *Airport Improvement Program* of the FAA and whose volume exceeds 10 million US Dollars, must be evaluated with a cost-benefit analysis, as documented in FAA (2019). Similarly, Jorge and de Rus (2004) present a framework for the evaluation of airport infrastructure projects by means of cost-benefit analyses. In the context of ASP-related applications, cost-benefit analyses have been applied to evaluate airport improvements (Landau et al., 2010), taxiway infrastructure projects (Daniel, 2002), baggage carousels (Yoon & Jeong, 2015) or airport security infrastructure (Stewart & Mueller, 2014).

2.4.1.4 Payback methods

Payback methods examine how long a project has to generate revenues until the initial expenses are recouped (Remer & Nieto, 1995b). Payback methods find some application in the area of airport infrastructure projects, such as the evaluation of multi-airport systems (De Neufville, 1995) or the selection of airports which are suitable for an expansion (Berawi et al., 2018).

2.4.1.5 Accounting methods

Finally, accounting methods are "primarily accounting concepts of a project's profitability" Remer and Nieto (1995b, p. 116), such as "accounting profit, book value, average book value and depreciation". Airport-related applications of accounting methods are not further discussed in this study, since they are usually company-specific.

For the evaluation of facility requirements, not all of the indices of merit listed above are used equally often in the literature. Indeed, according to Luss (1982), Martínez-Costa et al. (2014) and Van Mieghem (2003), most studies on the conventional CEP use (i) the net present value of an organisation or a project, (ii) the present value of the total resulting operating profit or (iii) the sum of the present values of all incurring costs. All of these methods are based (at least in part) on describing the future costs and revenues of a system or project. For this reason, the next section examines the costs and revenues that can transpire over the entire planning period of engineering systems in general and airport passenger terminal facilities in particular.

2.4.2 Cost and revenue functions

In CEP models, a large number of different cost and revenue sources of engineering systems are taken into account. For a good overview, the reader is referred to Geng and Jiang (2009), Julka et al. (2007), Martínez-Costa et al. (2014), Van Mieghem (2003) and Wu et al. (2005). In this section, costs and revenues relevant for airport passenger terminal facilities are discussed in more detail.

2.4.2.1 Installation costs

Installation costs, or investment costs, describe the costs arising from the installation of ΔK_i units of capacity at facility i. As explained by Luss (1982), installation costs CI_t can be described by a number of different cost functions, such as the *fixed charge* cost function or the *power cost* function. Fixed charge installation costs for airport passenger terminal facility i are defined as

$$CI_t\left(\Delta K_{i,t}\right) = \begin{cases} 0 & \text{if } \Delta K_{i,t} = 0 \\ ci_0 + ci_K \Delta K_{i,t} & \text{if } \Delta K_{i,t} > 0 \end{cases} \tag{2.9}$$

where $\Delta K_{i,t} = K_{i,t} - K_{i,t-1}$ describes the capacity adjustment for facility i in planning phase t, ci_0 are the fixed costs associated with any capacity adjustment irrespective of $\Delta K_{i,t}$, while ci_K are unit installation costs which describe the average cost per unit of capacity. In airport-related applications, fixed charge installation cost functions have been used by Chen and Schonfeld (2013) in order to describe the installation costs of new airport gates, by Solak et al. (2009) for airport passenger terminal facilities, as well as by Sun (2016) and Sun and Schonfeld (2015, 2016, 2017) to model installation costs of airport infrastructure in general.

To capture EoS effects, which describe the decreasing marginal costs of large capacity adjustments, a power cost function in the following form is often applied in the literature (Luss, 1982; Van Mieghem, 2003)

$$CI_t\left(\Delta K_{i,t}\right) = ci_K \cdot \left(\Delta K_{i,t}\right)^{\alpha_K} \tag{2.10}$$

where $0 < \alpha_K \leq 1$ is the *EoS factor*, which describes the extent of the savings that are achieved by EoS. At $\alpha_K = 1$, no EoS savings are experienced, while at $0 < \alpha_K < 1$, EoS savings are realised. Indeed, the closer the value chosen for α_K is to zero, the more pronounced are the EoS savings. According to Cardin and Hu (2016), a reasonable range for α_K for real-world engineering system projects is $0.6 < \alpha_K \leq 1$.

2.4.2.2 Operating costs

Operating costs describe the costs that arise from the operation and maintenance of a facility. To this end, Martínez-Costa et al. (2014) differentiate between *production-operating costs* and *holding-maintenance costs*. While the former consist basically of processing and production costs (Bihlmaier et al., 2009; Geng et al., 2009; Mitra et al., 2014) or material, labour and overhead costs (Thomas & Bollapragada, 2010), the latter specify the costs of keeping an inventory (Geng et al., 2009; Luss, 1984; Zhang et al., 2012), as well as maintenance costs (Luss, 1982; Rajagopalan, 1998).

Most authors model operating costs as a linear function of operational capacity $K_{i,t}$ and/or demand $d_{i,t}$

$$CO_t\left(K_{i,t}\right) = co_{K,i}K_{i,t} \qquad CO_t\left(K_{i,t}, d_{i,t}\right) = co_{K,i}K_{i,t} + co_{d,i}d_{i,t} \tag{2.11}$$

where $co_{K,i}$ and $co_{d,i}$ are the unit operating costs per unit of capacity and demand, respectively. In airport planning applications, operating costs as defined in Equation 2.11 are used by a number of authors. For instance, Sun (2016) and Sun and Schonfeld (2015, 2016, 2017) model operating costs of airport facilities, Ju et al. (2007) determine operating costs of passenger terminal facilities, or Adacher and Flamini (2020) and Adacher et al. (2017) calculate the operating costs of facilities used by departing passengers in an airport passenger terminal and check-in desks in particular.

2.4.2.3 Delay costs

When facilities are experiencing high levels of utilisation, which happens when demand is close to or even above the maximum throughput of a system, congestion and delays occur. The relationship between the utilisation of a facility and the expected level of delay which may result is extremely non-linear: the closer demand is to the maximum throughput of a plant, the faster waiting times and queues grow (De Neufville et al., 2013).

In order to quantify the disadvantages caused by congestion, delay costs are often specified. The determination of such costs depends significantly on the system under consideration. In systems where storable goods are produced, for example in manufacturing, delay-related costs can arise due to shortages, inventories and back-orders (Angelus & Porteus, 2002; Atamtürk & Hochbaum, 2001; Martínez-Costa et al., 2014; Rajagopalan & Swaminathan, 2001; Van Mieghem, 2003). However, in applications where "goods" cannot be stored, such as in communication networks or in the service industry, the use of inventories and stocks is not a viable option. As such, it is impossible to store telephone calls or to backlog passengers in an airport passenger terminal. In these circumstances, two distinct methods to specify delay-related costs are mentioned in the literature: (i) pricing the experienced waiting times, or (ii) pricing the provision of over-capacity or under-capacity.

The first approach, which is based on two steps, considers the discomfort and inconvenience which customers are exposed to in a congested facility. In the first step, the expected (average) waiting time of the customers is estimated by either applying analytical models, queueing system models or simulation models (Wu & Mengersen, 2013). In a second step, the estimated waiting times are transformed into waiting-related costs.

Regarding analytical models, the literature presents approaches to estimate congestion levels by means of approximation functions and queueing system models. As can be inferred from the name, approximation functions estimate the non-linear relationship between utilisation and delay. For instance, Solak (2007) and Solak et al. (2009) use triangular, parabolic and half-elliptical functions to approximate the relationship between the passenger flow rate through a passenger terminal facility and the resulting maximum delay experienced by passengers. In a similar manner, walking times in passageways are approximated using a deterministic function which expresses free-flow walking speed as a function of pedestrian density. Sun (2016) and Sun and Schonfeld (2015, 2016, 2017) apply non-decreasing and convex "facility performance functions", i.e. an analytical model, to describe the relationship between capacity utilization and delays.

Queueing system models are based on a mathematical description of the non-linear relationship between utilisation and delay (Hopp & Spearman, 2011). For airport-related applications, a large number of different queueing system model types are presented, both deterministic as well as stochastic in nature (Wu & Mengersen, 2013). For instance, Chen and Schonfeld (2013) apply a $M/G/1$ queueing system[7] to model delay costs experienced at congested airport gates and Suryani et al. (2010) approximate delay costs of congested runways with an $M/G/1$ queueing system.

Analytical models and queueing system models are based on simplifications and assumptions, for which reason these models usually require very little computing time. However, with analytical models and queueing system models it is not possible to consider dynamic effects affecting congestion and delays. For example, the estimation of delays for a number of interconnected and interdependent passenger terminal facilities can be very challenging or even impossible. In order to take such complex dependencies into account, simulation models, such as DES models are used in the literature. For

[7] The literature uses *Kendall's notation* to classify queueing system models. This notation is based on three parameters: $A/B/m$. A describes the arrival process used, B specifies the service time distribution and m denotes the number of servers of a queueing system. For the $M/G/1$ queueing system mentioned here, this means that the arrival process is memoryless and described with a Poisson process, the service times are generally distributed and the queueing system consists of one single server (Hopp & Spearman, 2011).

instance, Yoon and Jeong (2015) present a capacity planning model for the baggage carousels of Seoul *Incheon* International Airport which makes use of a DES model to simulate delay levels in function of the provided capacity level and demand. However, planners must be aware that simulation models often come with high computational requirements and an increased need for input and parametrisation (Janic, 2007).

Once the waiting times have been estimated with one of the approaches mentioned above, delay costs can be determined accordingly. In practice, the determined average waiting time is often multiplied with an estimated unit delay cost, which quantifies the cost of a hour's wait of a single passenger. According to Sun and Schonfeld (2015) and Yoon and Jeong (2015), suitable values for unit delay costs applicable to airport applications are provided in Jorge and de Rus (2004) or Martín and Voltes-Dorta (2011).

The second approach to quantify delay costs mentioned in the literature is based on the collection of penalty costs for oversized and/or undersized systems. Here, both the provision of unneeded capacity which remains unused over large periods of time as well as the provision of too little capacity which can lead to delays and congestion, is penalised. Saffarzadeh and Braaksma (2000) present an "optimum resource utilization model for passenger terminal buildings" which couples a DES model of the terminal with a capacity planning model. For given demand and capacity levels, Saffarzadeh and Braaksma determine the resulting LoS of the passenger terminal facilities with the DES model. If sub-optimal LoS levels are achieved, this circumstance is sanctioned with penalty costs. For this purpose, the provision of too many or too few units is determined and multiplied with a corresponding unit penalty cost which is based on "historical data" and determined with "engineering judgement" (Saffarzadeh & Braaksma, 2000, p. 77).

2.4.2.4 Revenues

Various CEP models also consider revenues $\mathcal{R}_t$ (Hiller & Shapiro, 1986) or the net profits generated by a company, a process or facility (Chen & Lu, 2012; Geng et al., 2009; Lim, Abdul Manan et al., 2013; Lim, Manan et al., 2013; Wang et al., 2008). In airport-related applications, the literature often estimates revenues generated from passengers by multiplying the number of passengers, i.e. the demand, with a constant unit revenue factor (Ju et al., 2007).

2.4.3 Conventional capacity expansion problem

DMs are interested in determining facility requirements which are *optimal*. This refers to facility requirements that lead to the best value of the index of merit selected, such as the largest NPV, the greatest profits or the lowest costs. For this reason, the selection of optimal facility requirement is an optimization problem known as the *capacity expansion problem (CEP)*. This section explains how optimal conventional facility requirements can be determined using so-called *conventional CEP models*. Section 2.4.4 then discusses the *flexible CEP models* that can be used to determine optimal flexible facility requirements.

As explained in Section 2.1.2, conventional facility requirements can be viewed as schedules which define when (timing) and how (size, types) capacity is adjusted by means of expansions and extensions or, if need be, the decommissioning and removal of existing infrastructure in order to meet demand over a certain planning horizon T of a strategic planning project (Luss, 1982; Van Mieghem, 2003). For airport passenger terminal facility i conventional facility requirements can therefore be formally expressed with a capacity vector $\mathbf{K}_i = [K_{i,1}, K_{i,2}, \ldots, K_{i,T}]$, which specifies the operational capacity $K_{i,t}$ in each planning period $t = 1, 2, \ldots, T$. Thus, the goal of a conventional CEP model is to determine the optimal capacity vector $\mathbf{K}_i^*$, which ultimately leads to the highest value of the index of merit selected. The resulting optimization problem is often complicated by the fact that capacity is usually considered *indivisible* (Dixit & Pindyck, 2012; Van Mieghem, 2003), which means that it can only be provided in whole units[8]. Furthermore, capacity is a non-negative property by definition, meaning that the provision of negative capacity is not possible. Consequently, each element $K_{i,t}$ of capacity vector $\mathbf{K}_i$ must be a

[8]For example, airports can only install either 3 or 4 check-in desks, and consequently, it is impossible to install 3.2 check-in desks.

non-negative integer

$$K_{i,t} \in \mathbb{N}_0 = \{0, 1, 2, \ldots\}. \tag{2.12}$$

The literature presents a large number of different types of conventional CEP models. The simplest CEP models are based on the seminal paper of Manne (1961), which "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" in order to determine *when* and *how* capacity should be adjusted best over time in order to meet demand (Luss, 1982, p. 908). While Manne (1961) focuses solely on capacity expansions, the literature also mentions conventional CEP models that allow for capacity reductions (Eppen et al., 1989), capacity replacement, depreciation and degradation (Rajagopalan, 1998), infrastructure renewal (Benedito et al., 2016), technology replacement (Wang & Nguyen, 2017), outsourcing (Rajasekharan & Peters, 2000) or a combination of these. Besides the timing and sizing of capacity adjustments, CEP models might also consider the types of capacity and the location where capacity is to be provided best (Martínez-Costa et al., 2014; Van Mieghem, 2003). CEP models which consider more than one type of capacity, such as different machines or different technologies are known as *multi-type* CEP models. Such models are, for example, presented by Ahmed and Sahinidis (2003) and Karabuk and Wu (2003). In contrast, *multi-location* CEP models consider the provision of capacity at different geographic locations (Bhutta et al., 2003; Bihlmaier et al., 2009; Eppen et al., 1989; Fleischmann et al., 2006; Shulman, 1991). Consequently, multi-location CEP models often also deal with transportation issues, since they are often applied to global manufacturing problems, such as the optimal definition of a global car production network (Fleischmann et al., 2006). For most ASP-related purposes, both multi-type as well as multi-location CEP models can be ignored, since airports usually do not deal with various types of capacity provided simultaneously, (e.g. different means to conduct the security check of passengers), and operate at one location only.

In the literature, a distinction is made between three different CEP model types: (i) stationary models, (ii) infinite time horizon models and (iii) finite time horizon models. Stationary models determine optimal capacity levels independently of time by applying *queueing models* or *newsvendor models* (Van Mieghem, 2003). They are best suited for applications in industries with short life cycles, such as the high-tech industry (Wu et al., 2005). For ASP applications, however, stationary capacity planning models might not be suitable due to the comparatively long life cycles of airport infrastructure.

Infinite time horizon models aim to determine optimal capacity levels over an infinite planning horizon. The most fundamental infinite horizon capacity planning model is presented in the seminal paper by Manne (1961), who determines the optimal capacity relief size and relief interval given deterministic demand. For a more in-depth overview on infinite time horizon CEP models, the reader is referred to Freidenfelds (1981) and Luss (1982). To the author's best knowledge, infinite time horizon capacity planning models have not been applied in the field of ASP.

Finite time horizon models, which are reviewed by Martínez-Costa et al. (2014), are defined for a planning horizon T, which is further divided into a finite number of planning periods $t = 1, 2, \ldots, T$. Finite time horizon models "seek answers for when and how much capacity to build in a dynamically changing environment", which explains their frequent use in the literature (Wu et al., 2005, p. 130). The basic structure of a finite time horizon model is shown below using the example of a CEP model for an airport passenger terminal facility i. The example is based on the assumption that the NPV is used as the index of merit. For a general overview on the topic and for further information on applications of conventional CEP models in other fields, the reader is referred to Geng and Jiang (2009), Julka et al. (2007), Martínez-Costa et al. (2014), Van Mieghem (2003) and Wu et al. (2005).

The literature further distinguishes between deterministic and stochastic CEP models. Deterministic CEP models do not consider uncertainty or the "stochastic nature of the inputs and parameters of the [model's] formulation", while the opposite is true for stochastic CEP models (Martínez-Costa et al., 2014, p. 73).

2.4.3.1 Deterministic capacity expansion problem

Deterministic CEP models do not take into account inputs or parameters that are subject to uncertainty but assume only one single version of the future. Assuming that (i) DHL demand $\mathbf{d}_i$ for airport passenger terminal facility i is known for all planning periods t within a given planning horizon T, and (ii) the NPV of facility i has been selected as the index of merit by which facility requirements are evaluated, a deterministic finite time horizon CEP model for facility i is defined as follows:

$$\underset{\mathbf{K}_i}{\arg\max} \quad NPV\left(\mathbf{K}_i, \mathbf{d}_i\right) \tag{2.13a}$$

$$\text{s.t.} \quad K_{i,t} \in \mathbb{N}_0 \tag{2.13b}$$

where capacity vector $\mathbf{K}_i = [K_{i,1}, K_{i,2}, \ldots, K_{i,T}]$ is the decision variable of the optimization problem. To ensure indivisibility and non-negativity of capacity, all elements $K_{i,t}$ of the capacity vector are restricted to $\mathbb{N}_0$, as indicated in Constraint 2.13b. Further, arg max denotes an operation that chooses $\mathbf{K}_i$ such that the objective function, i.e. $NPV\left(\mathbf{K}_i, \mathbf{d}_i\right)$, is maximized.

The inputs, i.e. the demand, and the constraints of the above-mentioned model are deterministic, and, as previously mentioned, deterministic CEP models are not capable of considering uncertainty. Indeed, Model 2.13 is based on the formulation of one single version of the future, expressed with DHL demand vector $\mathbf{d}_i$. Therefore, planners quite often use average values for parameters or single most probable future outlooks as input data for deterministic CEP models. However, this approach is somewhat problematic, since one might "fall into the trap of the *flaw of averages*" (De Neufville & Scholtes, 2011, p. 16). The *flaw of averages*, also known as *Jensen's inequality*, states that the evaluation of a design or a model based on the expected or average scenario is generally not equal[9] to the expectancy of the evaluations of all possible scenarios describing probable future

[9] Please note that inequality does not hold when the function or model is linear.

developments (Savage & Markowitz, 2009). In order to take all possible future developments into account, inputs or parameters of CEP models must therefore be described stochastically.

2.4.3.2 Stochastic capacity expansion problem

To consider uncertainty, the deterministic CEP presented in Model 2.13 is extended to a stochastic CEP model by means of a stochastic program, in which the objective function, the inputs or the constraints are subject to uncertainty that is expressed with (multi-dimensional) random variables $\boldsymbol{\xi} \sim \mathcal{F}$. The random variables are assumed to follow known probability distributions $\mathcal{F}$ (Bakker et al., 2020). The goal of a stochastic programming model is to determine the stochastically optimal value of the decision variable. This refers to the value of the decision variable that minimizes or maximizes the expected value $\mathbb{E}[\cdot]$ of the objective function. Therefore, Model 2.13 can be extended to a stochastic CEP model as follows:

$$\underset{\mathbf{K}_i}{\arg\max} \quad \mathbb{E}_{\boldsymbol{\xi} \sim \mathcal{F}} \left[NPV \left(\mathbf{K}_i, \boldsymbol{\xi} \right) \right] \tag{2.14a}$$

$$\text{s.t.} \quad K_{i,t} \in \mathbb{N}_0 \tag{2.14b}$$

Stochastic CEP models are either expressed as *two-stage* or as *multi-stage* problems, both of which are based on the concept of *recourse*. In a two-stage stochastic CEP model, some capacity expansion decisions are taken prior to the observation of any uncertainty, and as a consequence of these decisions, the expected value of the objective function is minimized or maximized after the uncertainty has been disclosed. In this way, decisions made at the first stage can be optimized by means of recourse actions at the second stage. Multi-stage stochastic CEP models are a generalisation of two-stage models (Birge & Louveaux, 2011) which allow DMs to "capture the dynamics of real-world decision making" better (Bakker et al., 2020, p. 3). As such, in a multi-stage stochastic program, recourse decisions are made sequentially in such a way that "every recourse decision [in stage t] will be selected based on the expected value of this decision for stage $t-1$ assuming that every future decision will be optimal" (Torres-Rincón et al., 2021, p. 5). In a multi-stage case, random variable ξ is extended to a stochastic process whose realisations follow a known probability distribution $\mathcal{F}$.

2.4.3.3 Deterministic counterpart to the stochastic capacity expansion problem

Stochastic CEP are very hard to solve, especially if the probability distributions under examination are continuous and the model consists of multiple stages. For this reason, so-called *scenario-trees* (Dupačová et al., 2000) are often introduced in order to discretise the underlying stochastic process by means of a number of scenarios $s = 1, 2, \ldots, S$ which describe possible realisations of the stochastic process over all stages or planning phases $t = 1, 2, \ldots, T$. In this study, a scenario s is expressed by means of vector $\boldsymbol{\xi}^s = \left[\xi_1^s, \xi_2^s, \ldots \xi_T^s\right]$. By introducing a finite number of scenarios $\boldsymbol{\xi}^s$, the stochastic CEP model presented in Equations 2.14 can be transformed into its *deterministic counterpart* (Bakker et al., 2020), which is defined as follows:

$$\underset{\mathbf{K}_i}{\text{arg max}} \quad \sum_{s=1}^{S} p_s \left(NPV\left(\mathbf{K}_i, \boldsymbol{\xi}^s\right)\right) \tag{2.15a}$$

$$\text{s.t.} \quad \boldsymbol{\xi}^s \in \Omega, \tag{2.15b}$$

$$K_{i,t} \in \mathbb{N}_0, \tag{2.15c}$$

$$p_1 = p_2 = \ldots = p_S, \tag{2.15d}$$

$$0 \leq p_s \leq 1, \tag{2.15e}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{2.15f}$$

where p_s expresses the occurrence probability of scenario $\boldsymbol{\xi}^s$, which, for the purpose of this study, is equal for all scenarios.

2.4.3.4 Solution procedures

Solving a conventional CEP model means that the optimal value of the decision variable is determined. Unfortunately, the literature does not present one universally applicable solution procedure but rather a large number of different solution procedures, some of which are very application-specific.

Deterministic CEP models expressed as linear programs can be solved with special algorithms, such as the simplex algorithm (Dantzig, 1955). Quite often, however, conventional CEP models are too complex to be solved within reasonable time. For this reason, authors introduce so-called relaxations, which are simplifications of the optimization problem that allow for a more efficient solution procedure. For example, an integer program can be relaxed to a linear program. Another way to simplify an optimization problem is to divide it into several small sub-problems, which are easier to solve (Birge & Louveaux, 2011). Moreover, the objective functions of non-linear CEP models, e.g. non-linear cost functions, are often relaxed by means of linear approximations, as for instance carried out by Sun and Schonfeld (2015).

Stochastic CEP models are even more complex to solve than deterministic CEP models. For this reason, stochastic CEP models are often converted into their deterministic counterparts by the introduction of a finite number of scenarios of uncertainty in order to simplify the solution procedure. Subsequently, the deterministic counterpart can be further simplified with the above-mentioned methods for deterministic CEP models.

According to Martínez-Costa et al. (2014), the solution procedures applied in the literature have evolved over time. Before the year 2000, a majority of authors applied either approximate algorithms or heuristics. Approximate algorithms are efficient procedures based on a mathematical proof that enable the determination of *good* solutions to the optimization problem whose distance to the optimal solution is less than a guaranteed value. In contrast, heuristics, which can also be used to determine good solutions, cannot provide any information on the quality of the solution. After the year 2000, authors predominantly used commercial solvers, such as *CPLEX*, *Xpress-MP* or the solver of *Microsoft*

Excel (Martínez-Costa et al., 2014). For very complex problems which, for instance, have non-linear objective functions, a large number of variables and/or large numbers of constraints, Martínez-Costa et al. (2014) report the usage of the genetic algorithm (GA), which is a meta-heuristic belonging to the class of *evolutionary algorithms*. GAs enable the near-optimal solution of complex optimization problems by means of processes observable in natural evolution, i.e. selection, reproduction, crossover and mutation (Bäck, 1996; Fogel, 2006; Holland, 1992; Michalewicz, 2013).

2.4.3.5 Applications of conventional CEP models

Conventional CEP models are used for a large number of applications, such as among others in manufacturing (Julka et al., 2007; Martínez-Costa et al., 2014), the heavy industries (Ulstein et al., 2006), the electronics and semiconductor industry (Geng & Jiang, 2009; Wu et al., 2005), the chemical or pharmaceutical industry (Mitra et al., 2014), the automotive industry (Bihlmaier et al., 2009; Fleischmann et al., 2006), the consumer goods industry (Rajagopalan & Swaminathan, 2001), telecommunications (Gendreau et al., 2006), the oil industry (MirHassani & Noori, 2011), electricity and power generation (Parpas & Webster, 2014), network design (Pimentel et al., 2013), urban transportation network design (Farahani et al., 2013), urban water resource systems (Mortazavi-Naeini et al., 2014) or seaports (Dekker et al., 2011).

In terms of airport-related applications, a number of relevant studies are mentioned in the literature. Solak (2007) and Solak et al. (2009) present a holistic passenger terminal CEP model which considers the capacity of the terminal to be optimal if the processing and walking times for passengers are as short as possible. This model is based on a multi-commodity flow network by means of which the processing and walking times are determined, subject to the provided capacities and stochastic demand. To simplify the non-linear relationship between facility utilisation and delays, Solak (2007) and Solak et al. (2009) make use of analytical approximation functions. Their proposed multi-stage stochastic CEP model is subsequently solved with a specifically developed heuristics solution algorithm. Sun (2016) and Sun and Schonfeld (2015, 2016, 2017) present stochastic CEP models for airport facilities such as airport terminals, runways and cargo facilities; these aim to minimize the sum of investment, operational and delay costs incurred over the entire planning horizon. Here, delay costs, which are modelled as non-linear functions, are linearised with the *outer-approximation technique*, and subsequently the model is solved by means of commercial solvers such as *CPLEX* (Sun & Schonfeld, 2015, 2017) or *FICO-Xpress* (Sun & Schonfeld, 2016).

In addition to these models mentioned above, which can be applied to several different airport (terminal) facilities, the literature also covers facility-specific CEP models. Chen and Schonfeld (2013) determine optimal capacity for airport passenger terminal gates by means of an analytical model which enables planners to determine the optimal timing and sizing of gate capacity adjustments in such a way that the total system costs are minimized. For this model, which considers uncertainty in demand and construction lead times, an analytical solution is presented. Finally, Yoon and Jeong (2015) suggest a CEP model for the determination of optimal facility requirements for the baggage carousels at Seoul International Airport in the Republic of Korea. Facility requirements are considered to be optimal if they maximize the cost-benefit ratio of the facility. The benefits of an expansion project are quantified in the potential savings in waiting times experienced by passengers. To this end, a DES model of the baggage carousel facility is used to calculate the resulting waiting times as a function of the provided capacity and demand. In terms of costs, Yoon and Jeong use construction and installation costs of capacity adjustments. Because only 23 different candidate flexibilities are considered, optimal capacity is determined with the *enumeration technique*.

2.4.4 Flexible capacity expansion problem

Conventional CEP models come with a serious limitation; they do not consider management interactions (Čulík, 2016; Schachter & Mancarella, 2016). Indeed, with conventional CEP models, one single (stochastically) optimal capacity vector is defined and then applied. Therefore, conventional facility requirements prevent DMs from adapting the plans to changing circumstances as uncertainty is disclosed. Put differently, conventional facility requirements do not allow planners "to capitalize on good fortune or to mitigate loss" (Brealey et al., 2008, p. 58), since they are not able to "adapt if the actual situations do not follow the modelled scenarios" (Cardin & Hu, 2016, p. 2). Because conventional facility requirements are rigid and do not allow for management interaction, they cannot be used for flexible engineering systems which are based on real options.

This section describes how to create facility requirements for flexible engineering systems. Such flexible facility requirements are able to take into account active decision-making processes. Thus, flexible facility requirements give planners and DMs the possibility to adapt the engineering system to changing circumstances as uncertainty unfolds. This capability enables flexible facility requirements to increase the value of an engineering system (Brealey et al., 2008; De Neufville et al., 2008; Geltner & De Neufville, 2018; Schachter & Mancarella, 2016). In fact, studies have shown that engineering systems planned with flexible facility requirements perform between 10 % to 30 % better financially than systems planned with conventional facility requirements (De Neufville & Scholtes, 2011).

2.4.4.1 Real option analysis

To evaluate the economic value of real options, so-called *real options analysis (ROA)-methods*, which are in essence adaptations of valuation methods for financial options, are applied (Trigeorgis, 1996). According to Borison (2005), Mun (2002) and Schachter and Mancarella (2016), the literature categorises ROA methods either as (i) closed-form analytical equations, (ii) lattice models or (iii) simulation models.

Closed-form analytical equations, such as the *Black-Scholes options pricing model* (Black & Scholes, 1973), allow planners to estimate the price and therefore the value of a (European style[10]) financial option. The Black-Scholes-Model is based on a system of

[10]A European style option is a financial option which can only be exercised at its expiration date.

stochastic partial differential equations which "can be solved given a set of input assumptions" (Mun, 2002, p. 139). As such, the Black-Scholes model is "exact, quick, and easy to implement" (Mun, 2002, p. 188). However, it is "very specific in nature, with limited modelling flexibility", since it is specifically designed for an application with European options in mind (Mun, 2002, pp. 123–124).

To overcome the limited applicability of closed-form analytical equations, discrete-time approaches, known as *lattice models*, have been developed by Cox et al. (1979). In lattice models, the period up to the expiration date of an option is discretised into a finite number of intervals. Then the uncertain evolution of the price of an asset is modelled with a tree-like structure, i.e. a lattice, see Section 2.3.3. Given a lattice that describes all possible paths that the price of an option can take until reaching its expiration date, the value of an option is determined backwards, i.e. from the leaf nodes of the tree to the root node, in a *backward induction process* (Kang et al., 2016; Mun, 2002). Lattice models are simple to implement (at least binomial lattices) and flexible in their application. However, due to the fact that the tree must be described in its entirety, trees covering large numbers of intervals tend to be computationally demanding (Mun, 2002; Schachter & Mancarella, 2016). Furthermore, the assumption that option prices can only change by means of predefined paths might not hold for all practical applications (Mun, 2002).

To estimate real option values of very complex problems, the literature suggests the use of *Monte Carlo simulation* approaches (Boyle, 1977). With this procedure a large but finite number of possible paths describing the future evolution of the price of an option are randomly sampled by means of a *Monte Carlo simulation*. For each price path the exercise value of the option can be determined. Subsequently, by averaging the discounted exercise values of all scenarios, the value of the option today can be determined (Ross et al., 2012). In contrast to the Black-Scholes model and lattice models, Monte Carlo simulation models are capable of considering multiple sources of uncertainty which can "take any distribution shape" (Schachter & Mancarella, 2016, p. 265).

In the literature, ROA-methods are often applied to evaluate the value of research and development projects (Hartmann & Hassan, 2006; IJzerman et al., 2017; Perlitz et al., 1999; Weeds, 2002), patents (Schwartz, 2004), corporate strategies (Driouchi & Bennett, 2012; Smit & Trigeorgis, 2007), or to evaluate the value of investments in IT technology (Benaroch, 2002; Chen, Zhang et al., 2009), smart grids and energy systems (Pless et al., 2016; Schachter & Mancarella, 2016), or utilities (Marques et al., 2015), etc. There is also a substantial body of literature focusing on airport-specific applications of ROA-methods, for example to evaluate airport expansions (Balliauw & Onghena, 2020; Morgado et al., 2011; Oliveira et al., 2020; Smit, 2003; Xiao et al., 2017; Xiao et al., 2013, 2016), airport construction projects (Chambers, 2007; Neiva, 2009; Pereira et al., 2006), investments in air transportation infrastructure (Miller & Clarke, 2003, 2007, 2010), or to conduct cost-benefit analyses for airport projects (Rivey, 2007).

Even though ROA-based models have been used extensively, the application of standard ROA-models for engineering systems in general and the capacity planning of engineering systems in particular is criticised in the literature for a number of reasons. Cardin, Xie et al. (2017, p. 2) explain that these ROA-models usually "[rely] on assumptions that apply well to finance, but not necessarily to an engineering setting". Most importantly, path independence, which is a fundamental assumption of most lattice models, might not hold in the context of engineering systems (Cardin, Xie et al., 2017; Cardin, Zhang et al., 2017; Chambers, 2007; De Neufville & Scholtes, 2011; Wang & De Neufville, 2005). Path independence applied in standard lattice models states that "an increase followed by a decrease in the uncertain parameter leads to the same result as a decrease followed by an increase" (Chambers, 2007, p. 144). In strategic capacity planning, however, it cannot be assumed that DMs would decide in the same manner for both paths. On the contrary, different paths usually lead to completely different decision sequences. Furthermore, classic ROA is based on the assumption that options can be "bought and sold in a free market" (Chambers, 2007, p. 45). However, engineering systems are, unlike most financial assets, not tradable assets. Indeed, there exists no market in which engineering systems, such as nuclear power plants, highways, runways or airport passenger terminals can be bought and sold. For these reasons, Cardin, Zhang et al. (2017) conclude that standard ROA-methods are not applicable for the evaluation of flexible engineering systems. The literature alternatively suggests the use of decision rules.

2.4.4.2 Decision rules

To overcome the above-mentioned limitations of traditional ROA-models, a number of authors propose evaluating flexible engineering systems by means of "decision analysis and Monte Carlo simulations" (Cardin, Xie et al., 2017, p. 2). In essence, these methods are based on the simulation of a large number of scenarios $\boldsymbol{\xi}^s = \left[\xi_1^s, \xi_2^s \ldots, \xi_T^s\right]$ which describe possible paths of future developments of a variable or factor that is subject to uncertainty. For each scenario, the behaviour of how DMs exercise the real options of an engineering system, i.e. the flexibility of the system, is modelled by means of *decision rules* $\mathcal{D}_{\boldsymbol{\theta}}$, which are "heuristic-triggering mechanisms" (Cardin, Xie et al., 2017, p. 1) that "[aim] to emulate the decision-making process" of human beings (Cardin, Zhang et al., 2017, p. 227). Accordingly, "a decision rule can be abstracted as a function ... that maps each scenario of uncertainty ... to a capacity sequence" (Cardin & Hu, 2016, p. 3). Applied to the example of airport passenger terminal facility i, a decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ is a function which, for each scenario of uncertainty $\boldsymbol{\xi}^s$, specifies the optimal operational capacity $K_{i,t}^s$ to be provided in planning period t, given (i) the history or the path of the already disclosed uncertainty $\boldsymbol{\xi}_{[t]}^s = \left[\xi_1^s, \xi_2^s, \ldots, \xi_t^s\right]$ at point in time t, and (ii) the operational capacity $K_{i,t-1}^s$ at the beginning of period t

$$K_{i,t}^s = \mathcal{D}_{\boldsymbol{\theta}}\left(\boldsymbol{\xi}_{[t]}^s, K_{i,t-1}^s\right) \tag{2.16}$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \ldots]$ is the parameter vector of decision rule $\mathcal{D}_{\boldsymbol{\theta}}$. Both the structure and form of the decision rule, as well as the parametrisation $\boldsymbol{\theta}$ are unknown. Therefore, optimal flexible facility requirements for an engineering system are determined by finding both the best decision rule and the best parameters of this rule which ultimately "select[s] the best strategy for deploying capacity flexibly over time and space" (Cardin & Hu, 2016,

p. 2).

In the literature, four different types of decision rules are presented: *conditional-go decision rules* (Cardin & Hu, 2016; Cardin et al., 2015; Cardin, Xie et al., 2017; Cardin, Zhang et al., 2017; Zhang & Cardin, 2017), *linear decision rules* (Cardin, Xie et al., 2017), *non-linear decision rules* (Georghiou et al., 2019) and *constant decision rules* (Cardin, Xie et al., 2017). *Conditional-go decision rules* are similar to *if-then-else statements* used in computer programming. The *if*-statement is used to check certain conditions, such as whether the observed demand is higher than the current maximum possible throughput of a facility. Should the *if* statement be fulfilled, certain actions, which are defined in the *then*-part of the rule, are executed. Otherwise, the actions specified in the *else*-part of the rule are applied. In *linear decision rules*, the decision to be taken in planning period t and scenario s depends linearly on the already disclosed uncertainty $\boldsymbol{\xi}^s_{[t]}$ and the state of the system at the beginning of period t which is expressed in terms of the operational capacity $K^s_{i,t-1}$. Similarly, in a *non-linear decision rule*, a non-linear mapping function which depends on the disclosed uncertainty and the state of the system at the beginning of period t is applied. In contrast, in *constant decision rules*, the decision in phase t does not depend on the disclosed uncertainty up to stage t.

In the literature on flexible CEP models, the conditional-go decision rule finds wide application. For instance, conditional-go decision rules are used to evaluate flexible engineering systems that contain real options, such as multi-storey car parks (De Neufville et al., 2006), nuclear power plants (Cardin, Zhang et al., 2017), on-shore liquid natural gas production facilities (Cardin et al., 2015), infrastructure for emergency medical services (Zhang & Cardin, 2017) or waste-to-energy systems (Cardin & Hu, 2016; Cardin, Xie et al., 2017; Hu et al., 2018; Xie et al., 2014; Zhao et al., 2018). Most probably, conditional-go decision rules enjoy such frequent use as their *if-then-else*-structure "provides planners with straightforward and intuitive guidance" (Zhang & Cardin, 2017, p. 121). In contrast, linear, non-linear and constant decision rules are less frequently applied. One example is when Cardin, Xie et al. (2017) suggest a flexible CEP model for a waste-to-energy system in Singapore where capacity expansion decisions for one component of the system are determined with a linear decision rule. Further, Hu et al. (2020) and Hu and Guo (2019) use linear and non-linear decision rules, which they call "reward functions", in order to determine optimal flexible facility requirements for a waste-to-energy system in Singapore. The works of Hu et al. (2020) and Hu and Guo (2019) are discussed further in Section 2.4.4.4.

Similar to conventional facility requirements, the determination of optimal flexible facility requirements presents an optimization problem, which aims to determine the decision rule that maximizes the expected net present value (ENPV) of an engineering system (Cardin & Hu, 2016; Cardin et al., 2015; Cardin, Xie et al., 2017; De Neufville et al., 2006; Hu et al., 2020; Hu & Guo, 2019; Xie et al., 2014) or which minimizes the total costs of the system (Cardin, Zhang et al., 2017; Zhang & Cardin, 2017). In the literature, two different approaches are used to determine optimal flexible facility requirements. Both approaches, which are referred to in this study as the *empirical approach* and the *generative approach*, are discussed below.

2.4.4.3 Empirical approach

In an empirical decision rule-based approach, the structure of the decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ is defined a-priori[11] by "experienced experts" (Hu et al., 2018, p. 256). Given the structure of the decision rule, the aim of a flexible CEP model is subsequently to determine optimal values for all parameters $\boldsymbol{\theta}^* = [\theta_1^*, \theta_2^*, \ldots]$ of the rule. Consequently, following the basic principles of CEP models, the parameter vector is considered optimal if the ENPV of the engineering system is maximized, the profit is maximized or the total costs are minimized. To solve the optimization problem at hand, the literature mentions the use of (i) simulation-based methodologies, (ii) stochastic programming models and (iii) evolutionary optimization algorithms.

Monte Carlo simulation-based methodologies are strongly connected with the concept

[11] Cardin, Kolfschoten et al. (2013) present methods which allow the systematic definition and determination of decision rules on an empirical basis.

of enumeration, in which a number of different potential solutions to the optimization problem at hand, called solution candidates, are tested one after another. The solution candidates can either describe a certain system configuration (De Neufville et al., 2006; Hu & Cardin, 2015) or the parametrisation of a decision rule (Cardin et al., 2015). De Neufville et al. (2006) present a case study for flexible multi-storey car parks, which can be expanded at a later point in time by adding additional building levels. Given a conditional-go decision rule whose parameters are assumed to be known a-priori, De Neufville et al. use the enumeration method to test which flexible system design leads to the greatest ENPV of the system. With this method each individual system design is evaluated separately, and the configuration resulting in the highest system value is selected for implementation. In a similar manner, Hu and Cardin (2015) evaluate a number of centralised and decentralised flexible system designs for a waste-to-energy plant in Singapore. Based on a pre-defined conditional-go decision rule which has been parametrised by experts, Hu and Cardin identify the system design which results in the highest ENPV from a total of 2000 scenarios of potential future demand. Cardin and Hu (2016) and Cardin et al. (2015) determine the optimal parametrisation of a conditional-go decision rule applied to a waste-to-energy plant in Singapore by means of the enumeration technique. To limit the computational effort needed to solve the problem, the real-valued parameters are discretised and upper and lower boundaries are introduced. Subsequently, all possible combinations of the parameter vector are tested one after another and the parameter vector which leads to the best performing system in terms of the resulting ENPV of the system is selected for implementation. While the enumeration technique is simple and can be implemented in a straightforward fashion, this method has the disadvantage that the exhaustive evaluation of the entire solution space is computationally demanding. For this reason, enumeration does not usually perform well with problems that have large solution spaces (Cardin et al., 2015).

Stochastic programming models for flexible CEP model based on the empirical approach are presented by Cardin, Xie et al. (2017), Cardin, Zhang et al. (2017), Xie et al. (2014), Zhang and Cardin (2017) and Zhao et al. (2018). As explained by Shapiro et al. (2014) and Xie et al. (2014), multi-stage stochastic programming models must be used for flexible CEP models, as this is the only way to embed decision rules. Xie et al. (2014) present a flexible CEP model for a waste-to-energy plant in Singapore for which a stochastically optimal conditional-go decision rule is determined using a multi-stage stochastic programming model. In this case, Xie et al. consider two sources of uncertainty describing the demand for the system: the total amount of waste, modelled with GBM, and the recycling rate, modelled with a stochastic *S-curve function*. A similar flexible CEP model focusing on the same waste-to-energy plant in Singapore is presented by Cardin, Xie et al. (2017). This model considers two independent sources of uncertainty (food waste and organic waste, both modelled with GBM) and allows for the inclusion of two different types of flexibility. The models proposed by Cardin, Xie et al. (2017) and Xie et al. (2014) are solved by means of *Lagrangian decomposition*, which tends to be "time consuming if the number of scenarios [of uncertainty] is large" (Zhao et al., 2018, p. 555). Zhao et al. (2018) extended the works of Cardin, Xie et al. (2017) to a multi-facility flexible CEP model, which enables the consideration of adjustment and switching options. Moreover, this study takes into account annually recurring fixed costs, such as operating costs. Zhao et al.'s model is solved with a decomposition algorithm that is coupled with a stochastic approximation algorithm, which, according to the authors, enables savings in both computation time and memory usage. Zhang and Cardin (2017) suggest the application of a flexible CEP model for emergency medical services which is based on a multi-facility stochastic programming model. Uncertain demand for emergency medical services is expressed in terms of the incident arrival rate, here modelled with GBM. Using conditional-go decision rules, multiple flexible strategies such as the phased provision of capacities at different locations or flexible one-site capacity expansions are studied. To solve the proposed model, Zhang and Cardin apply a hybrid heuristic, which consists of a combination of *Bender's decomposition* and a *branch and bound algorithm*. Cardin, Zhang et al. (2017) also present a conditional-go decision rule-based flexible CEP model for nuclear power plants. The proposed approach here is based on a multi-stage stochastic programming model which is capable of considering two independent sources of uncertainty (electricity demand and the public's acceptance of nuclear technology) as well as three different flexible strategies (phasing of initial capacity installations, on-site expansions and life extensions of existing infrastructure). This model is subsequently solved with the *branch and bound* algorithm and the *CPLEX* solver. Although the solution procedures mentioned above are widely used in the field of flexible CEP models, they tend to be quite complex, since, the decision rules must be captured in the constraints of the model (Hu et al., 2018). Furthermore, the required computational resources must always be kept in mind. Especially if a large number of scenarios of uncertainty are considered, the problems to be solved tend to become very large in terms of the number of their constraints and variables, which increases the risk that such models become "unsolvable within a reasonable time" (Zhang & Cardin, 2017, p. 138).

To address the drawbacks of the solution procedures mentioned above, some authors have suggested approaches which are based on evolutionary optimization algorithms. Evolutionary optimization algorithms come with a number of advantages, such as (i) their ability to solve optimization problems with large solution spaces in an efficient manner and (ii) their capability of being able to handle non-linear objective functions and constraints (Bäck et al., 2018; Kramer, 2017). Hu et al. (2016) and Hu et al. (2018) propose a flexible CEP model for a waste-to-energy plant in Singapore where the optimal parameters of a conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ are determined with a differential evolution algorithm. This is a continuous global optimization algorithm based on the concepts of evolutionary optimization (Price et al., 2006; Price, 2016). In this way, an initial population of solution candidates describing the potential parameter vectors is evolved over the course of a number of generations in order to determine the optimal parameter vector $\boldsymbol{\theta}^*$ of the decision rule.

The empirical approach comes with one major disadvantage: the structure of the decision rule is defined a-priori based on expert knowledge. For this reason it is theoretically possible that the optimal solution can never be described using the chosen structure of the decision rule (Hu et al., 2018). In order to find the global optimum, not only must the optimal parametrisation be determined, but also the optimal structure of a decision rule. This is the focus of the generative approach, which will be discussed in the next section.

2.4.4.4 Generative approach

Hu et al. (2020) and Hu and Guo (2019) present flexible CEP models based on a *generative approach* in which both the stochastically optimal structure and parametrisation of decision rules are determined. To solve the optimization problem at hand, both studies apply *gene expression programming (GEP)*, which is an evolutionary algorithm originally developed by Ferreira (2001). GEP enables the "automatic generation of computer programs", such as heuristic rules, formulae, logical rules, mathematical expressions, etc. by applying "nature-inspired operators such as mutation and crossover" (Hu & Guo, 2019, p. 989), the optimal structure as well as the optimal parametrisation of these computer programs are determined in an iterative procedure.

Both Hu et al. (2020) and Hu and Guo (2019) apply a GEP-based modelling approach to determine optimal flexible facility requirements for a waste-to-energy plant in Singapore. The decision rule and its parametrisation are considered optimal in both studies if the ENPV of the plant is maximized over 5000 demand scenarios which are generated using GBM. The results suggest that, for decision rules created with the GEP-based model, the waste-to-energy plant has a slightly higher ENPV than when conditional-go decision rules are used. However, the results show a rather large variance, which, according to the authors, is an indication for the complexity of the optimization problem at hand.

2.5 Gap analysis

With regards to the strategic capacity planning framework for airport passenger terminal facilities proposed in this study, the following gaps in the literature can be identified:

Annual aggregated demand model. The literature on the recognition and modelling of uncertainty is well established. Especially in the field of flexible engineering systems, GBM is routinely used by many authors to generate large numbers of demand scenarios. For this reason, the theoretical foundations do not require further development to achieve the goals of this study. Rather, the available methods for the modelling of uncertainty need to be applied in the context of ASP in order to determine future annual aggregated passenger demand scenarios for an airport.

DHL demand model. To specify facility requirements for airport passenger terminal facilities, future annual aggregated demand forecasts must be converted into facility-specific DHL figures. The literature indicates two methods to achieve this goal, namely, the design day schedule method and the ratio method. The design day schedule is based on the determination of fictitious flight schedules for future days, which makes the method unsuitable for an efficient conversion of annual aggregated demand figures into DHL figures. In contrast, the ratio method "aims to model the relationship between the DHL and annual demand by means of constant ratios or regression models" (Waltert et al., 2021, p. 1), which makes the method perfectly suitable for such a conversion. "The ratio method is well documented in the literature and has found widespread application in airport strategic planning, where it is predominantly used to define overall DHL, which is the DHL of all departing, arriving or transit passengers in a passenger terminal" (Waltert et al., 2021, p. 2). However, to the author's best knowledge, the following gaps in the literature exist:

- "... the ratio method has yet to be applied to determine DHLs for specific airport passenger terminal facilities, e.g., check-in facilities, the security checkpoints, the border control facilities, etc." (Waltert et al., 2021, p. 2). Such a facility-specific application of the ratio-based method must necessarily take into account so-called capacity saturation effects, which occur at airports whose runway capacity is constrained for a number of reasons, e.g. due to operational, legal, environmental or political limitations.

- There is no ratio-based DHL model which is founded on actual, disaggregated and automatically collated (big) input data describing passenger flows in airport terminals.

Conventional and flexible CEP models. The literature on conventional CEP models is already very extensive. Also in the field of airport applications, there are already several authors who have published corresponding models. Therefore, with regard to conventional facility requirements for airport passenger terminal facilities, no gap in the literature can be identified. However, the methods available in the literature need to be adapted and subsequently applied for the strategic capacity planning framework presented in this study.

In the area of flexible CEP models, on the other hand, the situation is different. Few authors have used both the empirical approach and the generative approach to determine stochastic optimal flexible facility requirements for a number of different engineering systems, such as nuclear power plants, liquid natural gas facilities or waste-to-energy plants. To the best of the author's knowledge, however, the literature mentions no relevant scientific work dealing with the generation of flexible facility requirements for airport passenger terminal facilities.

Chapter 3

Research areas and research questions

In this chapter, the research questions investigated in this study are presented. Based on the aims and objectives defined in Section 1.2, three research areas are defined; these deal with (i) the demand module, (ii) the CEP module and (iii) the practical application of the strategic capacity planning framework developed in this thesis.

Research area 1 – Demand models. The first research area focuses on the demand module, which consists of two different demand models that allow airport planners to determine both annual aggregated demand scenarios for an airport, as well as the DHL demand scenarios for a certain airport passenger terminal facilities. As discussed in Section 2.3.3, the literature on models to determine annual aggregated demand scenarios, such as GBM, is already quite extensive. In contrast, the conversion of annual aggregated traffic into the DHL demand of an individual airport passenger terminal facility using the ratio-based approach, which takes into account the capacity saturation of airports, is not documented in the literature. Consequently, the research questions (RQs) of research area 1 are:

RQ1. *How can annual aggregated demand scenarios for ASP purposes be generated by means of GBM in the case of an individual airport?*

RQ2. *How to determine DHL demand scenarios for an individual airport passenger ter-*

minal facility by means of the ratio-based model that is based on aggregated annual demand scenarios and passenger flow observations acquired with an automated PTS?

RQ3. *How can the ratio-based modelling method be applied at airports where the runway system is capacity constrained?*

Research area 2 – Facility requirements. The second research area deals with the CEP module, which consists of a number of conventional and flexible CEP models by means of which conventional and flexible facility requirements for airport passenger terminal facilities can be generated. While conventional CEP models have already been applied in the literature to determine facility requirements for airport passenger terminal facilities, flexible CEP models, irrespective of whether they are based on the empirical approach or on the generative approach, have not yet been applied in the context of ASP. The RQs for research area 2 are therefore as follows:

RQ4. *Is it possible to adjust and subsequently apply existing conventional CEP models for the determination of conventional facility requirements for airport passenger terminal facilities?*

RQ5. *How can existing flexible CEP models based on either the empirical or the generative approach be modified in such a way that they can be used for the determination of flexible facility requirements for airport passenger terminal facilities?*

Research area 3 – Planning example ZRH Airport. The third research area of this study focuses on the application of the proposed strategic capacity planning framework for airport passenger terminal facilities in a real-world ASP planning example. In the course of this planning example, conventional and flexible facility requirements for the check-in facilities ZRH Airport in Switzerland are determined. The facility requirements created in this process are compared with each other in terms of the value they add to the system. Furthermore, the sensitivity of the proposed CEP models is tested accordingly. Thus, the RQs of research area 3 are as follows:

RQ6. *Is there a value in defining flexible facility requirements for the check-in facilities at ZRH Airport? If so, how much more valuable are flexible facility requirements compared to conventional facility requirements?*

RQ7. *What are the factors of greatest influence on facility requirements for check-in facilities at ZRH Airport?*

RQ8. *How are facility requirements for check-in facilities at ZRH Airport affected by changes in these factors?*

Chapter 4

Methodology

This chapter describes the methodology used for the strategic capacity planning framework for airport passenger terminal facilities presented in this study. The structure of the framework, which is illustrated in Figure 4.1, can be divided into two distinct modules, a demand module and a CEP module.

The demand module is used to generate annual aggregated demand forecasts for an airport and subsequently to convert these figures into DHL demand forecasts for specific airport passenger terminal facilities. To this end, Section 4.1 describes the GBM-based *aggregated annual demand model*, which is used to determine large numbers of scenarios describing possible future traffic developments at airports. Section 4.2 then introduces the *unsaturated DHL model* and the *saturated DHL model*, which allow the conversion of annual aggregated demand scenarios into DHL demand scenarios for specific airport passenger terminal facilities.

The CEP module consists of a valuation model as well as a number of conventional and flexible CEP models. The valuation model presented in Section 4.3 is used to estimate the financial value of a given facility requirement of an airport passenger terminal facility in terms of its resulting NPV over the entire planning horizon of an ASP project. Section 4.4 introduces a total of four conventional and flexible CEP models used to generate stochastically optimal facility requirements for airport passenger terminal facilities.

The conventional CEP models include the so-called *baseline model* and the *fixed model*. The baseline model is used exclusively for benchmarking purposes. It permits an objective comparison of the financial value of facility requirements created with different CEP models. The fixed model allows the determination of conventional facility requirements for passenger terminal facilities in the form of stochastically optimal capacity vectors. The flexible models include the *conditional-go decision rule model*, which is based on the empirical approach, and the *reward function decision rule model*, which is based on the generative approach. Both models enable the determination of stochastically optimal flexible facility requirements in the form of decision rules.

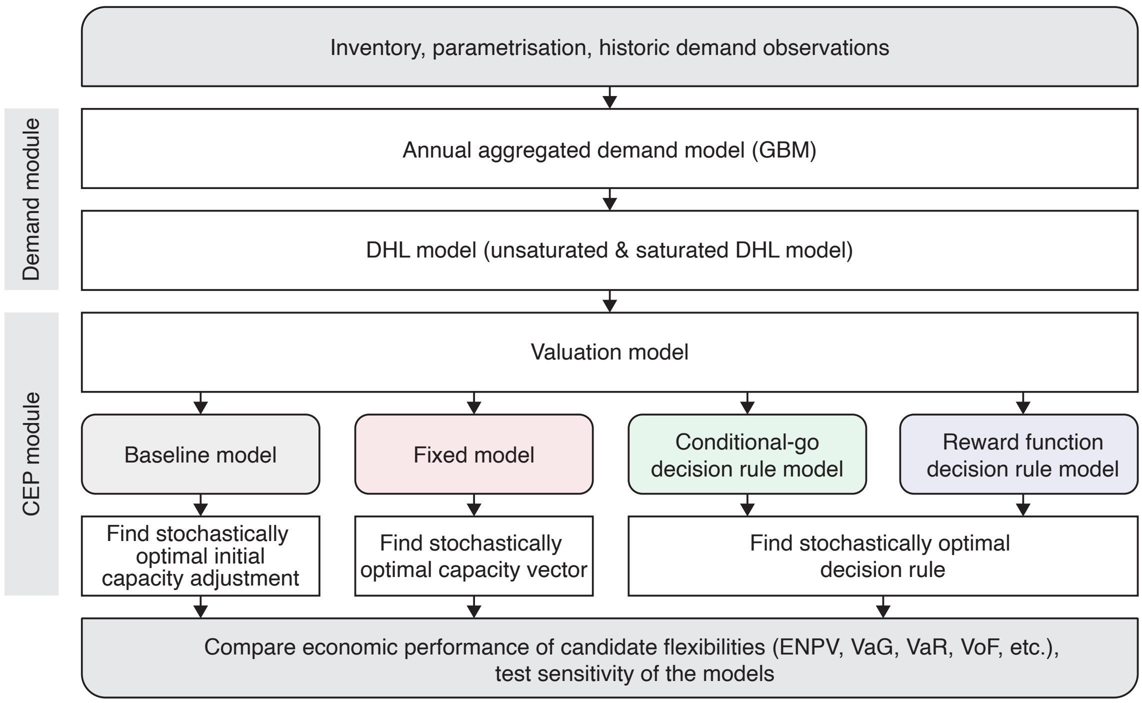

Figure 4.1: Proposed structure of strategic capacity planning framework consisting of a demand module and a CEP module.

4.1 Aggregated annual demand model

For most ASP projects, demand is expressed in the form of annual aggregated demand forecasts; these either specify the total number of passengers arriving and departing over the course of a year or the total number of ATMs handled at an airport in any year. The literature on engineering systems suggests diffusion models or lattice models in order to generate scenarios for annual aggregated demand forecasts (De Weck et al., 2007). Based on the literature overview presented in Section 2.3, it was decided to apply a diffusion model, or more precisely GBM, to model the annual aggregated passenger demand of an airport.

Demand over the entire planning horizon of an ASP project at a given airport can be expressed with a demand vector $\mathbf{D} = [D_1, D_2, \ldots, D_T]$. The elements D_t of vector $\mathbf{D}$ specify annual aggregated demand for planning periods $t = 1, 2, \ldots, T$. Demand observed at time $t = 0$ is designated as D_0 and is assumed to be known. The change in demand from planning period t to planning period $t+1$ is quantified with $\Delta D_t = D_{t+1} - D_t$. According to De Weck et al. (2007) and Mun (2002), the ratio between ΔD_t and D_t can be expressed with GBM[12] as

$$\frac{\Delta D_t}{D_t} = \mu_D \Delta t + \sigma_D \Delta W_t \tag{4.1}$$

where Δt is the interval between planning periods t and $t+1$, μ_D is the percentage drift rate of demand, σ_D is the percentage volatility of demand and ΔW_t refers to independent and identically distributed (i.i.d.) increments of the Wiener process[13].

To apply the model presented in Equation 4.1 to the generation of annual aggregated passenger demand forecast scenarios for an airport, it must be parametrised accordingly. To this end, the parameters D_0, μ_D and σ_D must be determined. Normally, initial demand D_0 is assumed to be the aggregated traffic volume of the year in which the forecast is made. The percentage drift rate and the percentage volatility are estimated on the basis of a number of historical annual aggregated passenger demand observations. According to De Weck et al. (2007), the mean drift rate $\hat{\mu}_D$ can be estimated with the sample mean of the observed historical data, while the volatility $\hat{\sigma}_D$ is estimated with the sample standard

[12]Please note: De Weck et al. (2007, p. 8) describe Equation 4.1 as "the time-discretized version of GBM".

[13]A Wiener process is often also referred to as Brownian motion.

deviation. The accuracy of these estimates depends largely on the number of historical demand observations used for the determination. According to Ahn and Fessler (2003), the standard error of the mean estimator $\hat{\sigma}_{\mu_D}$ can be estimated as follows:

$$\hat{\sigma}_{\mu_D} = \frac{\hat{\sigma}_D}{\sqrt{n}} \tag{4.2}$$

where n refers to the number of observations. Moreover, following Harding et al. (2014) the standard error of the standard deviation estimator $\hat{\sigma}_{\sigma_D}$ can be approximated as

$$\hat{\sigma}_{\sigma_D} \approx \frac{\hat{\sigma}_D}{\sqrt{2(n-1)}}. \tag{4.3}$$

For practical applications, Croghan et al. (2017) mention that at least $n = 100$ historical observations should be used to properly estimate the parameters of a GBM, while an even larger sample size in the order of magnitude of $n = 1000$ observations is preferable. However, since the focus of this study is on annual aggregated demand data from airports, it was not possible to take such large datasets into account, as the available data basis is simply not large enough. To this end, a sample size of $n = 11$ has been applied in this study.

Once the parameters of the proposed annual aggregated demand model, namely $\hat{D}_0$, $\hat{\mu}_D$ and $\hat{\sigma}_D$, have been estimated for a certain airport, planners are capable of determining a set $\Omega = \{\boldsymbol{\xi}^1, \boldsymbol{\xi}^2, \ldots, \boldsymbol{\xi}^S\}$ of randomly generated annual aggregated demand scenarios $\boldsymbol{\xi}^s = \left[\xi_1^s, \xi_2^s, \ldots, \xi_T^s\right]$ with Equation 4.1. Each vector $\boldsymbol{\xi}^s \in \Omega$ describes a possible aggregated annual passenger demand scenario for the airport of interest over all planning periods t considered in an ASP project.

4.2 Design hour demand model

To determine facility requirements for an airport passenger terminal facility, airport planners require information on its expected future DHL demand levels. For this reason, the aggregated annual passenger demand forecasts generated with the model presented in Section 4.1 must be converted into facility-specific DHL forecasts. For this conversion, a DHL model based on the ratio method, see Section 2.1.4, is presented in this section. The proposed model consists of two sub-models: (i) the *unsaturated DHL model*, which is used for airports that are not capacity constrained, and (ii) the *saturated DHL model*, which is used for airports whose runway system allows only a limited number of ATMs per year. Most of this section is based on the paper of Waltert et al. (2021), which was written and published as part of this study.

4.2.1 Input data

To develop the DHL models presented in this study, Waltert et al. (2021) explain that:

> ... input data originating from ZRH Airport and an equally sized European airport, referred to as *Airport 2*, have been used. The dataset provided by ZRH Airport covers the years 2009–2019, while the data provided by *Airport 2* covers the years 2012–2019. As such, the data provided can be divided into three distinct subsets: Annual data, ATM data and passenger flow data. The annual data provides passenger and ATM information aggregated on a yearly basis. To this end, the total number of enplanements (ATM and passengers) and the total number of departing passengers (the sum of local outbound and transit passengers) is provided. ATM data specifies the time of each movement and the number of local and transit passengers carried. Finally, passenger flow data, which is obtained by means of a passenger tracking system (PTS), describes the number of passengers entering a terminal facility [*i* in function of time of day]. (p. 4)

For the application proposed in this study, "PTS data originating from [automated] boarding pass readers installed at the entrance of the security [checkpoint facilities]" at ZRH Airport and *Airport 2* has been used due to its availability, good data quality and and seamless recording over the above-mentioned observation periods (Waltert et al., 2021, p. 5). It is assumed that the PTS data describing the influx in the security checkpoint is also applicable to describe the DHL of the check-in facility, since (i) all local passengers, i.e. the passengers using the check-in facility, are obliged to scan their tickets at the automated boarding pass reader to gain access to the security checkpoint and (ii) at both airports, the security checkpoint is located directly downstream of the check-in facilities. Consequently, the passenger flows in the check-in and security checkpoint facility are almost similar in magnitude and only show a slight time offset, which, however, can be neglected for the application presented in this study. Waltert et al. (2021) further elaborate as follows:

> The observed passenger influx data, which is measured with a PTS for facility i ... [and planning phase t], is expressed with a time series $d_{i,t}^P = \{d_{i,t,j}^P\}_{j=1}^{n_j}$, where $j = 1, 2, \ldots, n_j$ refers to 5-minute interval segments within year t. Each segment contains data on the total influx of passengers in the facility (e.g., number of passengers entering the security checkpoint from 11:45 to 11:50 on 02.04.2020)[14]. Subsequently, to smooth the 5-minute interval data, a w-moving sum $\overline{d}_{i,t}^P$ is defined as a new time series on $d_{i,t}^P$ by applying the *movsum* function provided in *Matlab*. The movsum function calculates the moving average for a sliding window of size w, which, for the application presented here, is selected specifically to ensure that each window covers 60 min of data (i.e. ±30 min around the timestamp of the 5-minute interval). In [Figure 4.2] an example of the observed data $d_{i,t}^P$ for the security checkpoint at ZRH Airport is shown as blue dots, while the moving sum $\overline{d}_{i,t}^P$ is displayed as a red line. (Note, the data is plotted on two different y-axes). (p. 4)

[14] Assuming a year with 365 days, $n_j = \frac{365\,\mathrm{d} \cdot 24\,\mathrm{h} \cdot 60\,\mathrm{min}}{5\,\mathrm{min}} = 105120$

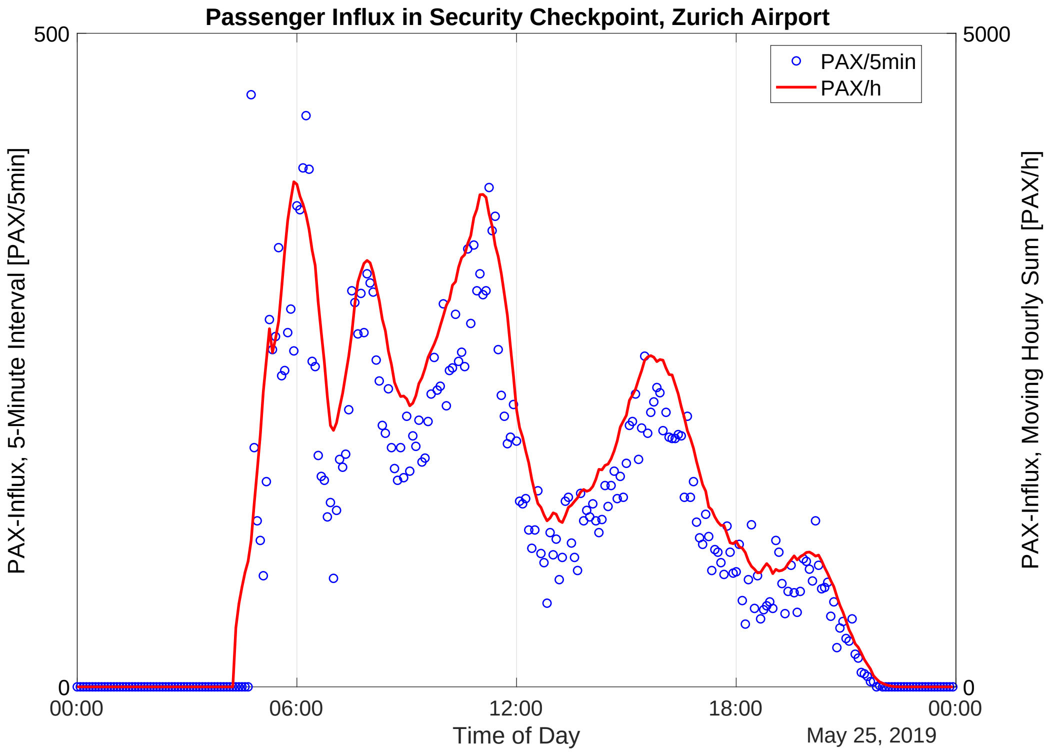

Figure 4.2: Observed 5-minute and hourly passenger inflows in security checkpoint at ZRH Airport. From Waltert et al. (2021, p. 4).

4.2.2 Calculation of DHL for passenger terminal facility

According to Waltert et al. (2021), the DHL of passenger terminal facilities is calculated as follows:

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

To meet this circumstance, the unsaturated and saturated DHL models presented in [Sections 4.2.3 and 4.2.4] can be applied to all DHL definitions without loss of generality. However, to provide the reader with a real-world example of the proposed planning methodology, the DHL definition as it is applied at ZRH Airport is used in this paper. At ZRH Airport the DHL for airport passenger terminal facilities is determined by means of the SBR referring to the 20$^{\text{th}}$ highest hour of passenger flow of the entire year. This contrasts with the literature, which recommends using the 30$^{\text{th}}$ highest hour for the SBR (Ashford et al., 2013; Matthews, 1995). According to ZRH Airport, the rationale behind opting for the SBR based on the 20$^{\text{th}}$ hour is grounded on considerations regarding the public's perception of service quality. Due to the operational concept of the local hub airline, most passenger terminal facilities at ZRH Airport experience only one daily peak period, whose duration is usually rather short. Consequently, by selecting a very restricting 20$^{\text{th}}$ highest hour for the DHL, the number of days on which customers might experience unacceptable service levels during this daily peak period can be limited significantly.

In light of this, for the purpose of this study the SBR for terminal facility i at [ZRH Airport or *Airport 2*] and for year t is calculated as follows. In a first step, the w-moving sum time series $\overline{d}_{i,t}^{P}$ of the observed passenger influx for facility i in year t is sorted in a descending order of the magnitudes of the observations. Then, this ordered list of hourly values is modified in an iterative procedure, which is referred to as the *rolling maximum algorithm*. Starting with the first value of the ordered list, which refers to the highest observed hourly passenger influx of the entire year, all values within ± 30 min from the timestamp of the first element of the list are removed from the list. Consequently, the algorithm iteratively applies the same procedure to the next element of the modified list until the end of the list is reached. An example is provided in [Figure 4.3], where the blue shaded elements of the ordered list are removed as they are within the specified time period of the first element of the list. In this way an ordered list of the maximum observed hourly passenger influxes into the facility of interest is generated. Finally, the SBR of facility i ... in year t, which is denoted as $d_{i,t}$, is defined by selecting the 20$^{\text{th}}$ highest element of the list modified with the rolling maximum algorithm. (pp. 4–5)

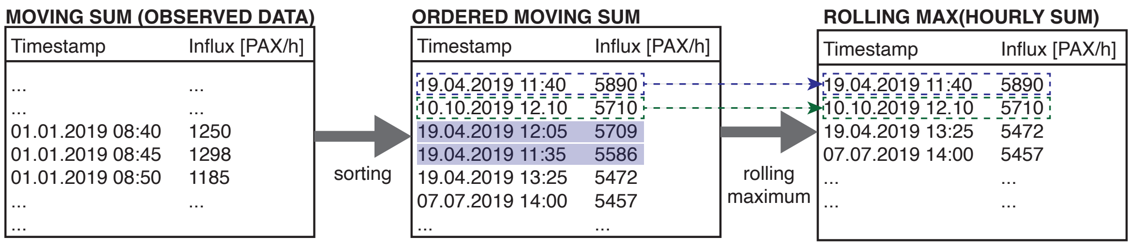

Figure 4.3: Proposed calculation procedure for DHL data based on observational data. From Waltert et al. (2021, p. 6).

4.2.3 Unsaturated DHL model

According to Waltert et al. (2021), the unsaturated DHL model is defined as follows:

Given the availability of (i) the observed DHL $d_{i,t}$ for airport passenger terminal facility i ... in year t for unsaturated demand conditions and (ii) the aggregated annual number of passengers D_t (see [Figure 4.4]), the transformation function of a linear regression model, called the *unsaturated DHL model*, is set out below:

$$d_{i,t}^{US} = \beta_{i,0}^{US} + \beta_{i,1}^{US} \cdot \ln D_t + \varepsilon_t^{US} \tag{4.4}$$

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

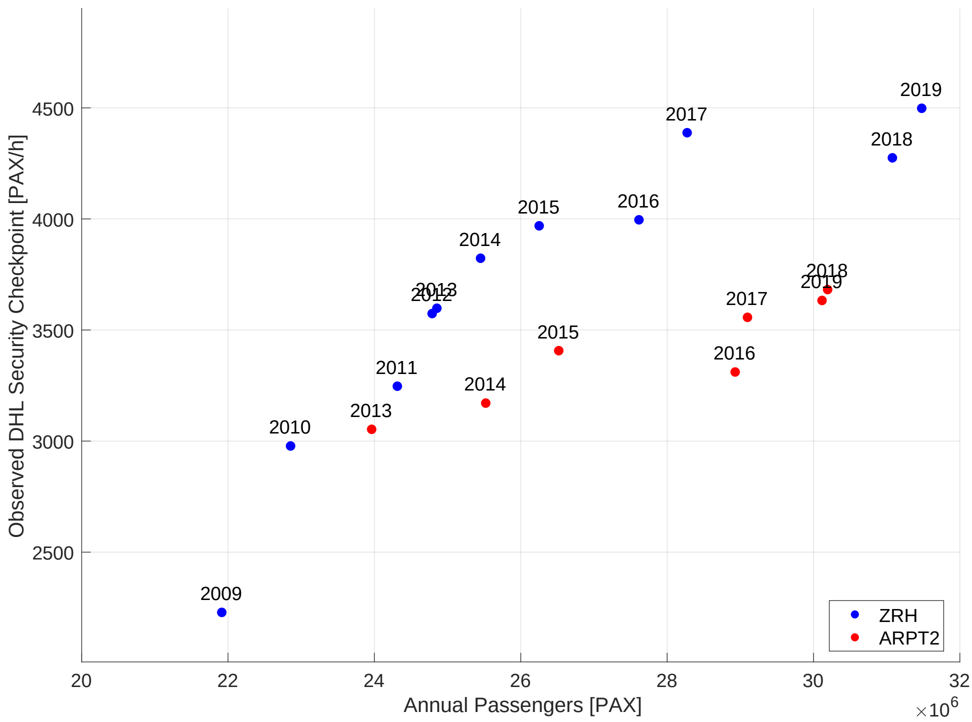

Figure 4.4: Observed DHL (20th peak hour) for ZRH Airport and *Airport 2*. From Waltert et al. (2021, p. 6).

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

> model the circumstances of such capacity constraints are taken into account. (p. 5)

4.2.4 Saturated DHL model

Waltert et al. (2021) define the saturated DHL model as follows:

> Many international airports are capacity constrained in terms of their runway system, which may only permit a maximum number of take-offs and landings per hour (De Neufville et al., 2013). Once this limit is reached, an airport can only grow to accommodate additional ATMs through substantially altering the performance of its runway system, for instance by building a new runway or by adopting new rules for runway usage, such as abolishing night curfews. Considering the airports included in this paper, the maximum hourly departure throughput of the runway system μ_R is known to be 44 and 41 movements per hour for ZRH Airport and *Airport 2* respectively.
>
> The number of passengers per ATM is limited and determined by a number of factors, among others the scheduled fleet mix of the airlines frequenting an airport. [Figure 4.5] shows the situation for 60 international airports[15], depicting the relationship between the average number of passengers per ATM and the annual passengers as well as the number of runways available at the respective airport. This number is used as a readily available proxy for the maximum throughput of a runway system. It can be inferred from [Figure 4.5] that the average number of passengers per ATM (i) seems to rise asymptotically to a certain limit value and (ii) appears to be influenced by the available number of runways at an airport.

[15] [Figure 4.5] is based on annual traffic data for both passengers and ATM of the following international airports: ABQ, AGP, AMS, ARN, ATH, ATL, AUH, BCN, BHX, BKK, BOS, BRU, BUD, BUR, CAN, CGN, CPH, DAL, DEN, DUB, DXB, EDI, FRA, GLA, HAM, HKG, ICN, LAX, LGA, LGW, LHR, LIN, LIS, LTN, MAD, MAN, MCI, MEL, MUC, MXP, ORD, ORY, OSL, PBI, PDX, PEK, PER, PMI, PRG, PVD, PVG, SAT, SFO, SIN, STN, SVO, SYD, VIE, WAW, YYZ and ZRH. The raw data has been sourced from (i) the Airport Statistics and Data Centre of Airport Council International (ACI) (https://aci.aero/data-centre/, Accessed: 28 December 2020) and (ii) Wikipedia.

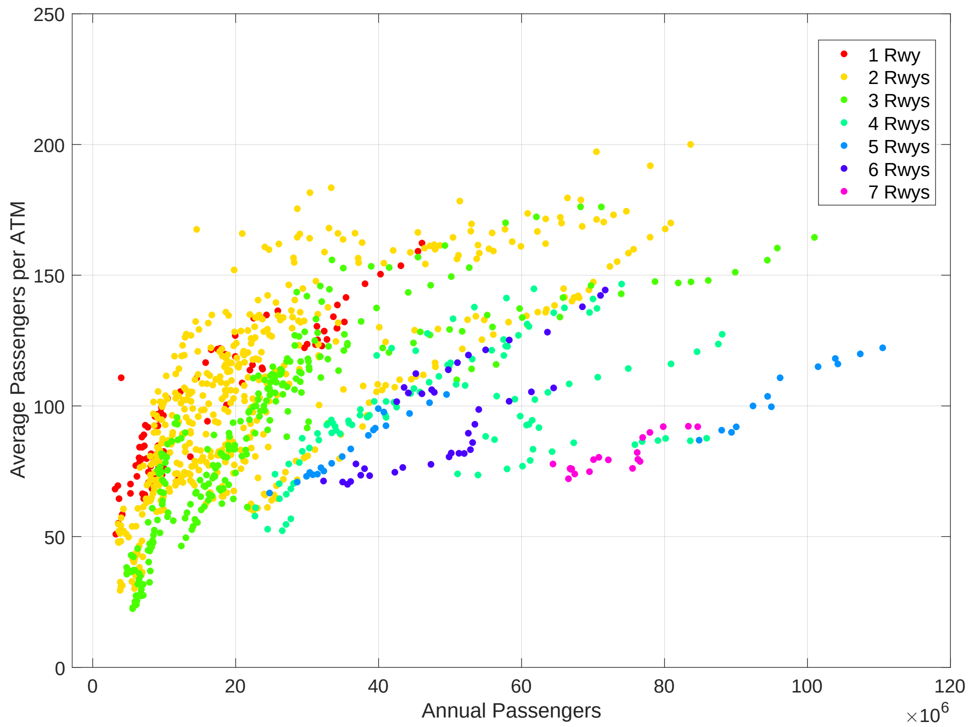

Figure 4.5: Average passengers per ATM in function of annual aggregated passengers of an airport and available number of runways. From Waltert et al. (2021, p. 6).

Consequently, this study uses a linear regression model to express the relationship between the annual average number of passengers per ATM $PAXATM_t$ for ZRH Airport and *Airport 2* versus the annual aggregated demand D_t measured in passengers, the year of observation t and the number of runways available at an airport of interest n_R. The transformation function of the proposed model is shown in [Equation 4.5]:

$$PAXATM_t = \beta_0^{PA} + \beta_1^{PA} \ln D_t + \beta_2^{PA} t + \beta_3^{PA} n_R + \varepsilon_t^{PA} \tag{4.5}$$

where $\beta_0^{PA}, \beta_1^{PA}, \beta_2^{PA}$ and β_3^{PA} are unknown coefficients and ε_t is the error term which is assumed to be normally distributed.

The linear regression model proposed in [Equation 4.5] specifies $PAXATM_t$, which is the annual average number of passengers per ATM. To determine the

DHL of facility i, the number of passengers per ATM using facility i during the design hour which is denoted as $PAXATM_{i,t}^{dh}$ must be known. The relationship between $PAXATM_{i,t}^{dh}$ and $PAXATM_t$ can then be described by means of ratio $r_{i,t}$

$$r_{i,t} = \frac{PAXATM_{i,t}^{dh}}{PAXATM_t}. \tag{4.6}$$

For the purpose of this study, historic observations of $PAXATM_{i,t}^{dh}$ for ZRH Airport and *Airport 2* are determined with PTS data originating from boarding pass readers installed at the entrance of the security checkpoints as well as ATM data provided by the airports. [Figure 4.6] depicts observational data for $r_{i,t}$ measured at ZRH Airport and *Airport 2* by means of boxplots in which the median of the observed ratio is illustrated with a red horizontal line.

As can be inferred from [Figure 4.6], the ratios $r_{i,t}$ for ZRH Airport and *Airport 2* seem to be subject to fluctuations and outliers. For reasons of simplicity in this study it is assumed that $r_{i,t}$ can be modelled with a constant which is estimated with the median of the observed data for $r_{i,t}$. The median has been chosen since it is known to be less susceptible to outliers than, for instance, the arithmetic mean.

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

$$d_{i,t}^{SA} = \mu_R \cdot PAXATM_t \left(D_t, t, n_R, \hat{\beta}_0^{PA}, \hat{\beta}_1^{PA}, \hat{\beta}_2^{PA}, \hat{\beta}_3^{PA} \right) \cdot \hat{r}_i \tag{4.7}$$

where μ_R is the maximum departure throughput capacity. This depends on the maximum number of take-offs per hour which can be handled by the runway system of an airport. $\hat{\beta}_0^{PA}, \hat{\beta}_1^{PA}, \hat{\beta}_2^{PA}$ and $\hat{\beta}_3^{PA}$ refer to the coefficient estimates of the linear regression model introduced in [Equation 4.5] and $\hat{r}_i$ is

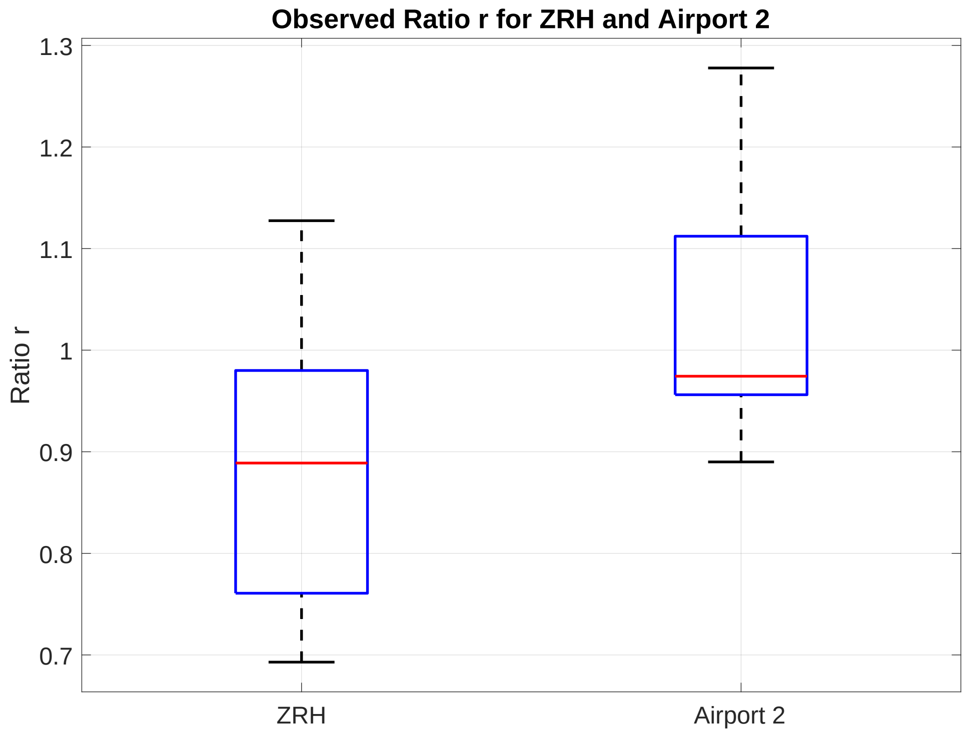

Figure 4.6: Example for ratio r between $PAXATM_{i,t}^{dh}$ and $PAXATM_t$ for ZRH Airport and *Airport 2*. From Waltert et al. (2021, p. 6).

the estimated value of ratio r_i. As such, for ZRH Airport, a ratio of $\hat{r}_i = 0.88$ and for *Airport 2*, a ratio $\hat{r}_i = 0.97$ is estimated. (p. 5)

4.2.5 Conversion of annual aggregated demand into DHL demand

With a fully parametrised DHL model for airport passenger terminal facility i, annual aggregated passenger demand scenarios $\boldsymbol{\xi}^s = [\xi_1^s, \xi_2^s, \ldots, \xi_T^s]$ created with the annual aggregated demand model presented in Section 4.1 can be converted into facility-specific DHL scenarios $\mathbf{d}_i^s = \left[d_{i,1}^s, d_{i,2}^s, \ldots, d_{i,T}^s\right]$. In order to do so, all annual aggregated demand scenarios $\boldsymbol{\xi}^s$ are first converted into an unsaturated DHL demand vector $\mathbf{d}_i^{s,US} = \left[d_{i,1}^{s,US}, d_{i,2}^{s,US}, \ldots, d_{i,T}^{s,US}\right]$ by using the unsaturated DHL model defined in Equation 4.4. They are also converted into a saturated DHL demand vector $\mathbf{d}_i^{s,SA} = \left[d_{i,1}^{s,SA}, d_{i,2}^{s,SA}, \ldots, d_{i,T}^{s,SA}\right]$ by making use of the saturated DHL model specified in Equation 4.7. In a second step, a DHL demand vector $\mathbf{d}_i^s = \left[d_{i,1}^s, d_{i,2}^s, \ldots, d_{i,T}^s\right]$ for facility i is created by comparing the unsaturated and saturated demand DHL vectors as follows:

$$d_{i,t}^s = \begin{cases} d_{i,t}^{s,US}, & \text{if } d_{i,t}^{s,US} \leq d_{i,t}^{s,SA} \\ d_{i,t}^{s,SA}, & \text{otherwise.} \end{cases} \tag{4.8}$$

For each planning phase t, a distinction is made as to whether unsaturated demand $d_{i,t}^{s,US}$ of facility i is less or greater than saturated demand $d_{i,t}^{s,SA}$. If unsaturated demand is less or equal to saturated demand, the facility is not affected by the airport system's capacity saturation. Consequently, the results of the unsaturated DHL model are used. However, for planning phases in which saturated demand $d_{i,t}^{s,SA}$ is greater than unsaturated demand $d_{i,t}^{s,US}$, the results of the saturated DHL model are applied. By repeating the procedure specified in Equation 4.8 for all sampled scenarios $\boldsymbol{\xi}^s \in \Omega$, annual aggregated demand forecasts of a given airport are converted into DHL demand forecasts for the airport passenger terminal facility i located at this airport.

4.3 Economic evaluation of facility requirements

As reviewed in Section 2.4.1, a number of indices of merit are available in order to economically evaluate facility requirements for engineering systems. Following the literature, for instance De Neufville and Scholtes (2011) and Geltner and De Neufville (2018), it was decided to evaluate facility requirements for airport passenger terminal facilities with the NPV in this study.

As discussed in Section 2.4.1, the NPV is defined as the sum of all discounted cash flows, i.e. costs $\mathcal{C}_t$ and revenues $\mathcal{R}_t$, which accumulate for a project or a system over a defined period of time

$$NPV = -\mathcal{C}_0 + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_t - \mathcal{C}_t\right) \tag{4.9}$$

where δ is the discount rate and $\mathcal{C}_0$ are initial costs incurred at $t = 0$. Equation 4.9

can be extended to apply to airport passenger terminal facilities. For this purpose, it is assumed that costs incurred and revenues generated by an airport passenger terminal facility i (i) can be forecasted, and (ii) depend mainly on the operational capacity $\mathbf{K}_i$ of facility i as well as its DHL demand $\mathbf{d}_i$. Consequently, the NPV of facility i is defined as follows:

$$NPV\left(\mathbf{K}_i, \mathbf{d}_i\right) = -\mathcal{C}_{i,0}\left(\Delta K_{i,0}, \Delta A_{i,0}\right) + \sum_{t=1}^{T}\left(\frac{1}{(1+\delta)^t}\left[\mathcal{R}_{i,t}(d_{i,t}, K_{i,t}) - \mathcal{C}_{i,t}(d_{i,t}, K_{i,t})\right]\right) \tag{4.10}$$

where $\mathcal{C}_{i,0}\left(\Delta K_{i,0}, \Delta A_{i,0}\right)$ refers to the initial installation costs incurred due to the installation of $\Delta K_{i,0}$ units of capacity and/or $\Delta A_{i,0}$ units of building space at $t = 0$. For the remainder of this section, the revenue functions $\mathcal{R}_{i,t}$ and cost functions $\mathcal{C}_{i,t}$ applied in Equation 4.10 are discussed in more detail.

4.3.1 Cost functions

Function $\mathcal{C}_{i,t}$ specifies the costs of facility i that are incurred during the design hour of planning phase t. Based on the works of Sun and Schonfeld (2015, 2016, 2017), the cost function $\mathcal{C}_{i,t}$ used in this study consists of 3 different sub-functions, as shown in Equation 4.11:

$$\mathcal{C}_{i,t} = CI_{i,t} + CO_{i,t} + CP_{i,t}. \tag{4.11}$$

The sub-functions are (i) installation costs $CI_{i,t}$, (ii) operating costs $CO_{i,t}$ and (iii) delay-related costs, which are referred to as penalty costs $CP_{i,t}$ in this study. In the following, all the cost drivers are considered individually.

4.3.1.1 Installation costs

Installation costs $CI_{i,t}$ are incurred when the capacity of a facility is adjusted by $\Delta K_{i,t}$ units of capacity and/or $\Delta A_{i,t}$ units of building space. In this case, the installation cost function consists of two terms: $CI_{i,t}^{\Delta K}$ describes installation costs generated by an adjustment of $\Delta K_{i,t}$ units of capacity, while $CI_{i,t}^{\Delta A}$ quantifies installation costs by building space changes to the amount of $\Delta A_{i,t}$:

$$CI_{i,t} = CI_{i,t}^{\Delta K} + CI_{i,t}^{\Delta A}. \tag{4.12}$$

Installation costs due to capacity adjustments. $CI_{i,t}^{\Delta K}$ describes the costs incurred if the operational capacity of facility i is changed by $\Delta K_{i,t} = K_{i,t} - K_{i,t-1}$ units of capacity. According to the literature reviewed in Section 2.4.2, a number of different types of installation cost functions are available. In this study, a combination of a *fixed charge function* and a *power cost function*, see Equations 2.9 and 2.10, is used. Besides EoS effects, project overhead costs, which typically arise in infrastructure projects due to planning and managerial tasks, are also considered for the determination of installation costs. In this study, overhead costs are modelled by means of a fixed percentage p_i^{ohd} of the installation costs. Consequently, the installation costs for adjusting the capacity of facility i by $\Delta K_{i,t}$ units of capacity are defined as

$$CI_{i,t}^{\Delta K} = \begin{cases} \frac{(1+p_i^{ohd})\cdot ci_{K,i}^{+}\cdot\left(\Delta K_{i,t}\right)^{\alpha_K}}{h_t}, & \text{if } \Delta K_{i,t} \geq 0 \\ \frac{(1+p_i^{ohd})\cdot ci_{K,i}^{-}\cdot\left(\Delta K_{i,t}\right)^{\alpha_K}}{h_t}, & \text{if } \Delta K_{i,t} < 0 \end{cases} \tag{4.13}$$

where $ci_{K,i}^{+}$ are unit installation costs for capacity expansions, $ci_{K,i}^{-}$ are unit dismantling costs for capacity reductions and α_K is the EoS factor for units of capacity of facility i. It should be noted that installation costs are divided by the total number of operational hours h_t in planning period t. The installation costs per operating hour, i.e. the design hour, are thus calculated.

Installation costs due to building space adjustments. Every change in the operational capacity of a facility by $\Delta K_{i,t}$ results in an adjustment of the required building space by $\Delta A_{i,t} = A_{i,t} - A_{i,t-1}$. The building area required by a passenger terminal facility comprises of the following factors: (i) space for the servers, i.e. check-in desks, baggage carousels, etc., (ii) queueing space for passengers and (iii) circulation space. The required building space for servers is defined as $\Delta K_{i,t} \cdot A_K$, where A_K is the required building space per server. According to the rule-of-thumb model presented in IATA (2017), building space required for passengers queueing in front of a facility depends on the expected maximum number of passengers Q_i^{max} in the queue, the LoS space standard $A_{Q,i}$, which specifies the minimal space provided for each passenger in the queue as well as the temporal LoS standard MQT_i, which specifies the acceptable average maximum queueing time per passenger in the queue. Following IATA (2017), Q_i^{max} is approximated as

$$Q_i^{max} = QF\left(MQT_i\right) \cdot d_{i,t} \cdot PK_i \tag{4.14}$$

where QF is a correction factor for the calculation of Q_i^{max}, $d_{i,t}$ is the DHL demand and PK_i is the peak 30-minute factor, which expresses the percentage of passengers that are handled within the 30 busiest minutes of the design hour[16]. The correction factor QF is defined as a piecewise function of the maximum queueing time MQT_i, as defined in Table 4.1.

MQT_i [min]	QF	CF
3	0.120	1.22
4	0.151	1.21
5	0.183	1.15
10	0.289	1.06
15	0.364	1.01
20	0.416	1.00
25	0.453	1.00
30	0.495	1.00

Table 4.1: Correction factor for demand variability CF and factor QF for the calculation of Q_i^{max}. Adapted from IATA (2017, p. 237).

[16]A peak 30-minute factor of $PK_i = 50\,\%$ means that the actual load during the design hour is equally distributed, since 50 % of all passengers are handled with the 30 busiest minutes of the design hour, while the other 50 % of the passengers are handled in the remaining 30 minutes of the design hour. However, a peak 30-minute factor of $PK_i = 100\,\%$ describes the situation, where all passengers handled during the design hour are processed within the 30 busiest minutes, while during the other 30 minutes, no passengers at all are processed. If not otherwise mentioned, in this study a peak 30-minutes factor of $PK_i = 50\,\%$ is assumed and applied.

Finally, circulation space consists of building areas required in order to facilitate the efficient movement of passengers within the premises of a facility. In airport planning, circulation space is usually specified as the percentage p_i^{circ} of the total building space of a facility which defines how much additional space is required for the circulation of passengers. Consequently, the building space adjustment $\Delta A_{i,t}$ caused by a capacity adjustment of $\Delta K_{i,t}$, can be described as follows:

$$\Delta A_{i,t} = \underbrace{\left(1 + p_i^{circ}\right)}_{\text{circulation}} \cdot (\underbrace{\Delta K_{i,t} \cdot A_K}_{\text{servers}} + \underbrace{Q_i^{max} \cdot A_{Q,i}}_{\text{queue}}). \tag{4.15}$$

In accordance with Equation 4.13, installation costs due to the adjustment of $\Delta A_{i,t}$ units of building space in facility i and planning period t are subsequently defined as

$$CI_{i,t}^{\Delta A} = \begin{cases} \frac{(1+p_i^{ohd}) \cdot ci_{A,i}^{+} \cdot \left(\Delta A_{i,t}\right)^{\alpha_A}}{h_t}, & \text{if } \Delta A_{i,t} \geq 0 \\ \frac{(1+p_i^{ohd}) \cdot ci_{A,i}^{-} \cdot \left(\Delta A_{i,t}\right)^{\alpha_A}}{h_t}, & \text{if } \Delta A_{i,t} < 0 \end{cases} \tag{4.16}$$

where $ci_{A,i}^{+}$ are unit installation costs for space expansion, $ci_{A,i}^{-}$ are unit dismantling costs for space reductions, α_A is the EoS factor for units of building space in facility i and h_t specifies the number of operational hours of facility i in planning period t.

Initial installation costs. Initial installation costs $\mathcal{C}_{i,0}$ arise when the capacity and the building space of facility i are adjusted at $t = 0$ by $\Delta K_{i,0}$ and $\Delta A_{i,0}$. Initial installation costs are calculated by means of Equations 4.13 and 4.16.

4.3.1.2 Operational costs

Operational costs CO_t specify the costs of operation of facility i during the design hour of planning period t. In this study, operating costs consist of four distinct terms: (i) operating costs per passenger, (ii) operating costs per units of capacity $K_{i,t}$, (iii) operating costs per unit of building space $A_{i,t}$ and (iv) operating costs per unit of building space used for retail purposes $A_{R,i,t}$. Consequently, in accordance with the literature reviewed in Section 2.4.2, operating costs are defined with the following linear function

$$CO_{i,t} = d_{i,t} \cdot co_d + K_{i,t} \cdot co_K + A_{i,t} \cdot co_A + A_{R,i,t} \cdot co_R \tag{4.17}$$

where co_d, co_K, co_A and co_R are unit operating costs per unit of demand $d_{i,t}$, capacity $K_{i,t}$, building space $A_{i,t}$ and retail space $A_{R,i,t}$. All unit operating cost factors are specified per operating hour h_t.

4.3.1.3 Penalty costs

Following the works of Saffarzadeh and Braaksma (2000), penalty costs $CP_{i,t}$ are incurred if the operational number of units of capacity $K_{i,t}$ is either considered *over-designed* or *under-designed*. Costs of over-designing the infrastructure arise if more infrastructure is provided than required, while costs of under-design arise if not enough infrastructure is provided. Therefore, penalty costs due to infrastructure under-design can be viewed as a means of translating congestion and delays into a monetary penalty, since the probability for delays is higher if the capacity of a system does not meet demand. In contrast, penalty costs due to infrastructure over-design can be viewed as an approach to penalise the provision of infrastructure which is not or only rarely used during the design hour, something which is inefficient from an economical point of view.

In this study, capacity is described as over-designed or under-designed if the resulting average waiting time experienced by passengers queueing for a facility i during the design hour of planning phase t fails to achieve temporal target LoS standard which is considered *optimal* by IATA (2017). The optimal target LoS range is defined by parameters MQT_i^{min} and MQT_i^{max} as indicated in Figure 4.7. Both MQT_i^{min} and MQT_i^{max} are parameters which can either be obtained from IATA (2017) or specified by airport planners to reflect local needs.

Once the optimal LoS range has been defined, the possibility of under-design or over-design can be determined. If the average waiting time experienced by passengers during the design hour is shorter than MQT_i^{min}, the infrastructure is considered to be over-

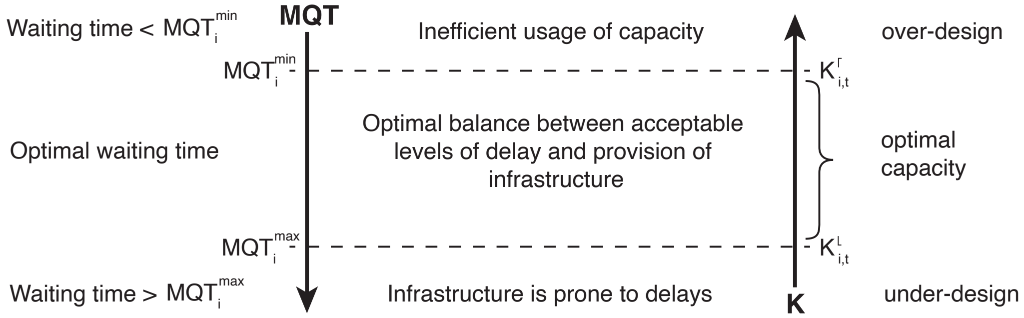

Figure 4.7: Definition of over-designed and under-designed capacity for determination of penalty costs CP_t.

designed. If, however, average waiting times occur that are longer than MQT_i^{max}, too little infrastructure has been provided and the facility is therefore considered to be under-designed. The capacity threshold levels where over-design or under-design conditions are reached can be determined using the rule-of-thumb capacity model provided by IATA (2017). Thus, given DHL demand $d_{i,t}$ of facility i in planning period t, average processing time PT_i of facility i as well as the peak 30-minute factor PK_i, the over-design threshold level $K_{i,t}^{\lceil}$ and the under-design threshold level $K_{i,t}^{\lfloor}$ are calculated as follows:

$$K_{i,t}^{\lceil} = \frac{d_{i,t} \cdot PK_i \cdot \frac{PT_i}{60}}{30 + MQT_i^{min}} \qquad K_{i,t}^{\lfloor} = \frac{d_{i,t} \cdot PK_i \cdot \frac{PT_i}{60}}{30 + MQT_i^{max}}. \tag{4.18}$$

If $K_{i,t}$, which is the operational capacity of facility i in planning phase t, is either greater than the over-design threshold level $K_{i,t}^{\lceil}$ or less than the under-design threshold level $K_{i,t}^{\lfloor}$, penalty costs are incurred. According to Saffarzadeh and Braaksma (2000), penalty costs are defined as follows:

$$CP_{i,t} = \begin{cases} \left(K_{i,t} - K_{i,t}^{\lceil}\right)^{\alpha_P} \cdot cp_i^{\lceil}, & \text{if } K_{i,t} \geq K_{i,t}^{\lceil} \\ \left(K_{i,t}^{\lfloor} - K_{i,t}\right)^{\alpha_P} \cdot cp_i^{\lfloor}, & \text{if } K_{i,t} < K_{i,t}^{\lfloor} \end{cases} \tag{4.19}$$

where α_P is a coefficient used to express the non-linearity of delay-related costs, as proposed by Sun (2016) and Sun and Schonfeld (2015, 2016, 2017). In this way, the provision of only slightly too much or slightly too little infrastructure can be priced differently from the provision of greatly over-sized or under-sized infrastructure. Furthermore, $cp_i^{\lceil}$ is the unit penalty cost for one over-designed unit of capacity and $cp_i^{\lfloor}$ is the unit penalty cost for one under-designed unit. For this reason, parameters $cp_i^{\lceil}$ and $cp_i^{\lfloor}$ must be determined by planners accordingly.

4.3.2 Revenue functions

Function $\mathcal{R}_{i,t}$ specifies revenues generated by facility i during the design hour in planning period t. Following the literature reviewed in Section 2.4.2, the revenue of an airport passenger terminal facility is thereby modelled with the following linear function

$$\mathcal{R}_{i,t} = d_{i,t} \cdot r_{PAX,i} + K_{i,t} \cdot r_{K,i} \tag{4.20}$$

where $r_{PAX,i}$ refers to unit revenues per design hour passenger, and $r_{K,i}$ are unit revenues per unit of operational capacity $K_{i,t}$. Both unit revenues are expressed per operational hour. For airport passenger terminal facilities, unit revenues per passenger are usually generated through passenger fees, while unit revenues per unit of capacity result from utilisation and rental fees paid by handling agents, airlines and other stakeholders.

The planning example, see Section 5, introduces flexible airport passenger terminal facilities which contain buffer spaces. These buffer spaces can be used temporarily for the provision of retail, food and beverage services. The revenues generated by offering such retail-related services can also be captured with a linear function. Thus, Equation 4.20 can be extended in the following way:

$$\mathcal{R}_{i,t} = d_{i,t} \cdot r_{PAX,i} + K_{i,t} \cdot r_{K,i} + A_{R,i,t} \cdot r_{R,i} \tag{4.21}$$

where $A_{R,i,t}$ is the buffer space in square meters and $r_{R,i}$ is the average retail revenue per unit of retail area per operational hour.

4.4 Capacity expansion problem models

In this section, four different CEP models for airport passenger terminal facilities are presented. The conventional CEP models discussed in Section 4.4.1 are used to determine stochastically optimal conventional facility requirements, while the flexible CEP models introduced in Section 4.4.2 allow the determination of stochastically optimal flexible facility requirements. As illustrated in Figure 4.8, conventional facility requirements are created for systems which do not contain real options and are therefore not flexible. Conventional facility requirements are described in the form of a single stochastically optimal capacity vector $\mathbf{K}_i^*$ which maximizes the ENPV of a facility over all scenarios of uncertainty $\boldsymbol{\xi}^s \in \Omega$ and planning phases t considered.

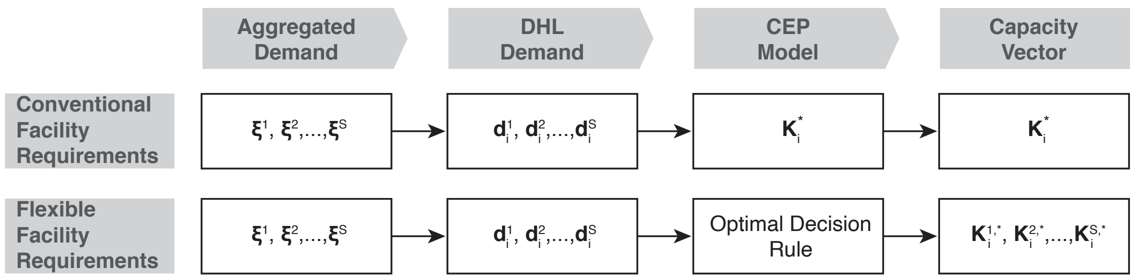

Figure 4.8: Generation process of conventional and flexible facility requirements for airport passenger terminal facilities by means of conventional and flexible CEP models.

In contrast, flexible CEP models are capable of determining optimal facility requirements for flexible engineering systems which make use of real options. Instead of defining one single stochastically optimal capacity vector, flexible CEP models aim to determine a stochastically optimal decision rule. For each scenario of uncertainty $\boldsymbol{\xi}^s \in \Omega$, the decision rule is applied on an individual basis to generate one single corresponding capacity vector $\mathbf{K}_i^1, \mathbf{K}_i^2, \ldots, \mathbf{K}_i^S$. In the following, the NPV of the system for scenario s is calculated based on demand specified in scenario $\boldsymbol{\xi}^s$ and capacity vector $\mathbf{K}_i^s$. Consequently, the decision rule is considered optimal if the resulting ENPV of the system over all scenarios of uncertainty is maximized.

4.4.1 Conventional CEP models

The conventional CEP models presented in this section are based on the deterministic counterpart of the stochastic CEP model presented in Equations 2.15 on page 71. Given the economic evaluation model for airport passenger terminal facilities proposed in the previous section, see Equation 4.10 on page 105, the deterministic counterpart of the stochastic CEP model is extended to

$$\underset{\mathbf{K}_i}{\arg\max} \quad \sum_{s=1}^{S} p_s \left(-\mathcal{C}_{i,0}(\Delta K_{i,0}, \Delta A_{i,0}) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_{i,t}(d_{i,t}^s, K_{i,t}) - \mathcal{C}_{i,t}(d_{i,t}^s, K_{i,t}) \right) \right) \tag{4.22a}$$

$$\text{s.t.} \quad \boldsymbol{\xi}^s \in \Omega, \tag{4.22b}$$

$$d_{i,t}^s = f(\xi_{i,t}^s, PAXATM_t, \mu_R, \hat{r}_i), \tag{4.22c}$$

$$K_{i,t} \in \mathbb{N}_0, \tag{4.22d}$$

$$p_1 = p_2 = \ldots = p_S, \tag{4.22e}$$

$$0 \leq p_s \leq 1, \tag{4.22f}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{4.22g}$$

where, Constraint 4.22b specifies annual aggregated demand scenarios created by means of the GBM-based model introduced in Section 4.1 and Constraint 4.22c defines how scenarios $\boldsymbol{\xi}^s \in \Omega$ are converted into DHL demand scenarios by means of the DHL model documented in Section 4.2. Constraint 4.22d ensures indivisibility as well as non-negativity of capacity. Furthermore, Constraints 4.22e, 4.22f and 4.22g define the probability of occurence of all demand scenarios.

Based on the deterministic counterpart of the stochastic CEP model shown above, two conventional CEP models are developed in this study: (i) the *baseline model*, which will be solely used for benchmarking purposes and (ii) the *fixed model*, which is used to determine stochastically optimal conventional facility requirements for airport passenger terminal facilities. In the following, the baseline model and the fixed model are discussed in detail. Additionally, a solution procedure is presented for both models.

4.4.1.1 Baseline model

Due to the baseline model being used for benchmarking purposes only, results generated with the fixed model, as well as the flexible CEP models introduced in Section 4.4.2.1, can be evaluated for their solution quality and for the value they add to the system, see Section 5.1.4.

Model formulation. The baseline model is founded on the assumption that the capacity of a facility can only be adjusted at time $t = 0$ by amount $\Delta K_{i,0}$. After this initial capacity adjustment, the capacity remains at a constant level of $K_{i,1} = K_{i,2} = \ldots = K_{i,T} = K'_{i,0} = K_{i,0} + \Delta K_{i,0}$ for the remaining duration of the ASP project. Thus, the CEP model presented in Equations 4.22 is simplified as follows:

$$\underset{\Delta K_{i,0}}{\arg\max} \quad \sum_{s=1}^{S} p_s \left(-\mathcal{C}_{i,0}(\Delta K_{i,0}, \Delta A_{i,0}) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_{i,t}(d^s_{i,t}, K'_{i,0}) - \mathcal{C}_{i,t}(d^s_{i,t}, K'_{i,0}) \right) \right) \tag{4.23a}$$

$$\text{s.t.} \quad K'_{i,0} = K_{i,0} + \Delta K_{i,0}, \tag{4.23b}$$

$$\xi^s \in \Omega, \tag{4.23c}$$

$$d^s_{i,t} = f(\xi^s_{i,t}, t, PAXATM_t, \mu_R, \hat{r}_i), \tag{4.23d}$$

$$K_{i,t} \in \mathbb{N}_0, \tag{4.23e}$$

$$-K_{i,0} \leq \Delta K_{i,0} \leq \Delta K_i^{max}, \tag{4.23f}$$

$$p_1 = p_2 = \ldots = p_S, \tag{4.23g}$$

$$0 \leq p_s \leq 1, \tag{4.23h}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{4.23i}$$

where Constraint 4.23b defines the capacity adjustment at time $t = 0$. The magnitude of this adjustment is limited by Constraint 4.23f. All other constraints are identical with the deterministic counterpart of the stochastic CEP model presented above. The aim of the baseline model is to find $\Delta K^*_{i,0}$, which is the stochastically optimal value for the initial capacity increment, so as to ensure that the ENPV of the system over all scenarios of uncertainty $\boldsymbol{\xi}^s \in \Omega$ is maximized. With the solution procedure documented below, the optimal value for $\Delta K_{i,0}$ is determined accordingly.

Proposed solution procedure. Capacity is considered both indivisible as well as non-negative, as specified in Constraint 4.23e. Because $K'_{i,0}$ must not be negative, the magnitude of $\Delta K_{i,0}$ is limited by Constraint 4.23f. To solve CEP models in which the number of potential solutions, also called *solution candidates*, is limited and known, the *enumeration* method is often used in practice, such as in Cardin and Hu (2016) and Cardin et al. (2015) and De Neufville et al. (2006). Here, enumeration is an umbrella term for algorithms that evaluate each possible solution candidate one by one and subsequently select the best one.

Software implementation. To solve the baseline model, Algorithm 1 has been developed for this study. The algorithm, implemented in the *Python* programming language (version 3.7.7), can be divided into two phases: an initialisation phase and a loop. During the initialisation phase, the parameters of the algorithm, such as the initially available capacity $K_{i,0}$, the maximum capacity adjustment size $\Delta K_{i,max}$, etc. are set. Next, S random demand scenarios are sampled with the annual aggregated demand model introduced in Section 4.1 and assigned to set Ω. The annual aggregated demand scenarios are converted into facility-specific DHL demand scenarios by means of the DHL model. Given the demand scenarios, the proposed algorithm loops over all feasible solution candidates as specified in Constraint 4.23f in order to evaluate their *fitness* in an iterative procedure. To this end, for each solution candidate, i.e. each feasible value of $\Delta K_{i,0}$, the resulting ENPV for facility i is calculated over all the demand scenarios $\mathbf{d}^1, \mathbf{d}^2, \ldots, \mathbf{d}^S$. Once the fitness of all feasible solution candidates has been evaluated, the solution candidate which results in the highest ENPV is considered the optimal solution candidate $\Delta K_{i,0}^{*}$.

Algorithm 1 Enumeration-based solver for baseline model

procedure BASELINESOLVER
    Initialise $K_{i,0}$ ▷ Initial capacity
    Initialise ΔK_i^{max} ▷ Upper bound for capacity development
    $ENPV^* \leftarrow 0$
    $\Delta K_{i,0}^* \leftarrow 0$
    Sample scenarios $\Omega \leftarrow \boldsymbol{\xi}^s$ ▷ Annual aggregated demand model
    Generate DHL scenarios $(\mathbf{d}^1, \mathbf{d}^2, \ldots, \mathbf{d}^S)$ ▷ DHL model
    for $\Delta K_{i,0} = -K_{i,0}$ to ΔK_i^{max} **do**
        for $s = 1$ to S **do**
            $NPV^s \leftarrow NPV(\Delta K_{i,0}, \mathbf{d}^s)$
        end for
        $ENPV(\Delta K_{i,0}) \leftarrow \mathbb{E}\left[NPV^1, NPV^2, \ldots, NPV^S\right]$
        if $ENPV(\Delta K_{i,0}) > ENPV^*$ **then** ▷ Keep best performing candidate
            $ENPV^* \leftarrow ENPV(\Delta K_{i,0})$
            $\Delta K_{i,0}^* \leftarrow \Delta K_{i,0}$
        end if
    end for
    return $\Delta K_{i,0}^*, ENPV^*$ ▷ Best solution candidate and corresponding ENPV
end procedure

4.4.1.2 Fixed model

The fixed model is used to create conventional and stochastically optimal facility requirements for an airport passenger terminal facility i. The facility requirements created with the fixed model are expressed in the form of a single stochastically optimal capacity vector $\mathbf{K}_i^* = \left[K_{i,1}^*, K_{i,2}^*, \ldots, K_{i,T}^*\right]$. This means that the same optimal capacity vector is applied to all demand scenarios $\boldsymbol{\xi}^s \in \Omega$, regardless of the future development of the factors which are subject to uncertainty.

Model formulation. In contrast to the baseline model, the fixed model allows for capacity adjustments in all planning phases $t = 1, 2, \ldots, T$. Therefore, the decision variable of the fixed model is capacity vector $\mathbf{K}_i$. Consequently, the stochastic counterpart of the CEP model presented in Equations 4.22 is adjusted as follows for the fixed model:

$$\underset{\mathbf{K}_i}{\arg\max} \quad \sum_{s=1}^{S} p_s \left(-\mathcal{C}_{i,0}(\Delta K_{i,0}, \Delta A_{i,0}) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_{i,t}(d_{i,t}^s, K_{i,t}) - \mathcal{C}_{i,t}(d_{i,t}^s, K_{i,t}) \right) \right) \tag{4.24a}$$

$$\text{s.t.} \quad \boldsymbol{\xi}^s \in \Omega, \tag{4.24b}$$

$$d_{i,t}^s = f(\xi_{i,t}^s, t, PAXATM_t, \mu_R, \hat{r}_i), \tag{4.24c}$$

$$K_{i,t} \in \mathbb{N}_0, \tag{4.24d}$$

$$\Delta K_{i,t} = K_{i,t} - K_{i,t-1}, \tag{4.24e}$$

$$-\Delta K_i^{max} \leq \Delta K_{i,t} \leq \Delta K_i^{max}, \tag{4.24f}$$

$$p_1 = p_2 = \ldots = p_S, \tag{4.24g}$$

$$0 \leq p_s \leq 1, \tag{4.24h}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{4.24i}$$

where capacity is non-negative and indivisible as stated in Constraint 4.24d. Moreover, capacity adjustments $\Delta K_{i,t}$ are defined in Constraint 4.24e and subsequently limited by Constraint 4.24f to a set of solution candidates. Since every capacity vector $\mathbf{K}_i$ consists of T elements which can each take on values from $-\Delta K_i^{max}$ to ΔK_i^{max} including zero, the number of potentially feasible capacity vectors, also referred to as the *solution space* of the fixed model, is $(2\Delta K_i^{max} + 1)^T$. This can result in the solution space becoming very large. For instance, if $\Delta K_i^{max} = 50$ units and $T = 20$ planning phases, the resulting size of the solution space is 101^{20}.

Proposed solution procedure. Because the solution space of the fixed model is significantly larger than that of the baseline model, it is computationally inefficient to use an enumeration-based solution procedure. For the determination of near-optimal solutions of the fixed model, a GA is applied, since, as discussed in Section 2.4.3.4, GAs are especially suitable for application within complex CEP models, i.e. models with large solution spaces, non-linear objective functions and non-linear constraints.

GAs belong to the class of *evolutionary optimization algorithms*, which are based on the three key principles of natural evolution; heredity, variation and selection (Bäck, 1996; Fogel, 2006; Holland, 1992; Michalewicz, 2013). In a GA, a *population* of solution candidates, also referred to as *phenotypes*, is modified over a finite number of *generations* $g = 0, 1, \ldots, G$ by means of natural evolution in such a way that increasingly better solutions to an optimization problem emerge. Each solution candidate describes a possible solution for the optimization problem, which, in the case of the fixed model, are capacity vectors that satisfy Constraints 4.24d, 4.24e and 4.24f. For the actual solution procedure of a GA, phenotypes must be first converted with an *encoding function* into corresponding *genotypes*, which are then represented as *chromosomes*. In case of the fixed model, chromosomes are defined as vectors $\mathbf{x} = [x_1, x_2, \ldots, x_T]$ whose elements x_t are referred to as *genes*. The genes of chromosomes used for the fixed model express the capacity adjustment $\Delta K_{i,t} = K_{i,t} - K_{i,t-1}$ of facility i in planning period t. Consequently, the encoding function for the fixed model, which transforms a phenotype $\mathbf{K}_i$ into a genotype $\mathbf{x}$, i.e. a chromosome, is expressed as

$$\begin{aligned} \mathbf{x} &= [K_{i,1} - K_{i,0}, K_{i,2} - K_{i,1}, \ldots, K_{i,T} - K_{i,T-1}] \\ \mathbf{x} &= [\Delta K_{i,1}, \Delta K_{i,2}, \ldots, \Delta K_{i,T}] = [x_1, x_2, \ldots, x_T] \end{aligned} \tag{4.25}$$

where $K_{i,0}$ is the operational capacity at $t = 0$, which is a parameter of the fixed model. To *decode* a chromosome $\mathbf{x}$ into a phenotype $\mathbf{K}_i$, an iterative procedure, defined in Equation 4.26, is applied. For this purpose, each element $K_{i,t}$ of the capacity vector forming a solution candidate $\mathbf{K}_i$ is calculated recursively as

$$K_{i,t} = K_{i,t-1} + x_t. \tag{4.26}$$

Given the *genetic representation* of solution candidates introduced above, the actual solution procedure of GAs can be discussed. This basically consists of two distinct phases as illustrated in Figure 4.9 and Algorithm 2: the *random generation of an initial popula-*

tion of solution candidates and the *evolutionary cycle* (Bäck et al., 2018; Kramer, 2017).

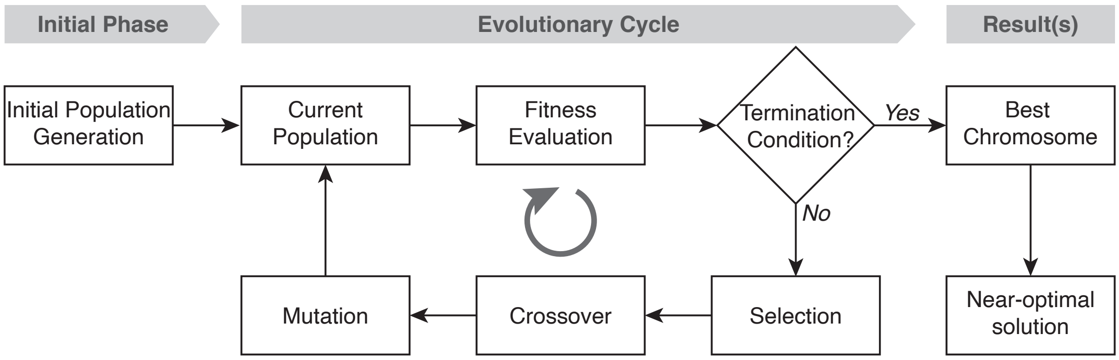

Figure 4.9: Basic principle and structure of a genetic algorithm based on an initial phase, the evolutionary cycle and the determination of a near-optimal solution.

Generation of initial population. In GAs, a population $P(g) = \left(\mathbf{x}_{1,g}, \mathbf{x}_{2,g}, \ldots, \mathbf{x}_{M,g}\right)$ consisting of $m = 1, 2, \ldots, M$ chromosomes $\mathbf{x}_{m,g}$ evolves over the course of $g = 0, 1, \ldots, G$ generations. Here, parameter M denotes the number of chromosomes of a population and parameter G the maximum number of generations. To initialise the solution procedure of a GA in generation $g = 0$, an initial population $P(0)$ of randomly generated solution candidates must be sampled. The literature suggests creating the chromosomes of the initial population in such a way that a large portion of the solution space of the optimization problem is covered (Kramer, 2017). For the fixed model, the genes from the chromosomes of the initial population are integers which are randomly sampled with uniform probability from the following set of feasible capacity adjustments denoted as

$$e = \{-\Delta K_i^{max}, -\Delta K_i^{max} + 1, \ldots, \Delta K_i^{max}\}. \tag{4.27}$$

Besides the generation of an initial population, annual aggregated demand scenarios $\boldsymbol{\xi}^s \in \Omega$ as well as DHL demand scenarios $\mathbf{d}^1, \mathbf{d}^2, \ldots, \mathbf{d}^S$ are created with the annual aggregated demand model introduced in Section 4.1 as well as the DHL demand model presented in Section 4.2. At this point, it is important to mention that for all generations, an identical set of demand scenarios is used.

Evolutionary cycle. As soon as an initial population $P(0)$ of randomly sampled chromosomes is available, the evolutionary cycle can commence. In a first step, all the chromosomes of the current population, which is the initial population in the first iteration of the evolutionary cycle, are *evaluated* for their *fitness*. The fitness of a chromosome is a measure of how well a certain solution candidate solves the optimization problem at hand. To determine their fitness value, all the chromosomes must first be decoded into phenotypes, i.e. capacity vectors, using Equation 4.26. Then, the capacity vectors are evaluated with the objective function of the fixed model, which is given in Equation 4.24a. In this way, the fitness value of the capacity vectors corresponds to their respective ENPV over all demand the scenarios generated initially.

Algorithm 2 Basic procedure for GA

procedure GA
    $g \leftarrow 0$ ▷ g refers to the generation
    Initialise $P(g)$ ▷ Create initial population
    while not terminating conditions **do**
        Evaluate $P(g)$
        Create $P'(g)$ from $P(g)$ with selection operator
        Create $P''(g)$ from $P'(g)$ with crossover operator
        Create $P'''(g)$ from $P''(g)$ with mutation operator
        $P(g+1) \leftarrow P'''(g)$
        Check termination conditions
        $g \leftarrow g+1$
    end while
    return best solution candidate
end procedure

Once all the chromosomes of the current population $P(g)$ have been evaluated for their fitness, an *offspring population* $P(g+1)$ is created by means of three different *genetic operators*, namely (i) the selection operator, (ii) the crossover operator and (iii) the mutation operator:

- The *selection operator* is responsible for selecting chromosomes from population $P(g)$ in order to form population $P'(g)$. The selection procedure is conducted as a random experiment in which chromosomes with high fitness values have higher chances to be selected for population $P'(g)$. In this study, the *tournament selection* method with a tournament size of 4 is used. Tournament selection is simple to implement and it can be applied in parallel computing applications (Bäck et al., 2018). These features are important for the actual software implementation, as it makes use of parallel computing capabilities to reduce the runtime of the proposed solution procedure. Another selection operator used in this study is *elitism*, which copies the best performing solution candidate of population $P(g)$ directly into population $P(g+1)$. In this way, the best performing solution candidate of the current generation is preserved.

- The *crossover operator* combines genetic information of two randomly selected *parental* chromosomes from offspring population $P'(g)$ in order to form two new *child* chromosomes, which are subsequently assigned to population $P''(g)$. Thereby, the parental chromosome's likelihood of being selected depends on their corresponding fitness value: the higher their fitness, the higher the probability of being selected. The crossover process is repeated until population $P''(g)$ contains the same number of chromosomes as population $P(g)$. In this study, the *two-point crossover* method is applied, since this is capable of preserving "important building blocks", i.e. segments within chromosomes (Bäck et al., 2018, p. 71). This feature is considered important, given the fact that chromosomes of the fixed model describe the timely evolution of capacity adjustments of facility i.

- The *mutation operator* randomly alters the information in genes of all chromosomes of population $P''(g)$ with probability p_M, which is a parameter of the GA (Bäck, 1996; Bäck et al., 2018). Population $P'''(g)$ is generated by applying the mutation operator to every chromosome of population $P''(g)$. In this study, a *uniform mutation operator*, which replaces the value of a gene with a randomly selected value from set e, is defined in Equation 4.27 where each element of set e has an identical likelihood of being drawn.

Termination condition(s). After the successful application of the genetic operators, offspring population $P(g+1)$ is created as $P(g+1) = P'''(g)$. Before repeating the whole evolutionary cycle once again, the GA checks whether one or more termination conditions have been reached in generation g. In this study, only one termination condition is checked, namely, whether the maximum number of generations G, which is a parameter of the fixed model, has already been reached. Consequently, once the maximum number of generations has been reached, the whole evolutionary cycle is terminated and the best solution candidate of population $P(G)$, i.e. the chromosome with the highest fitness value in population $P(G)$, is returned as the near-optimal solution of the fixed model. If the termination conditions have not been reached, the generation counter g is incremented by one and the entire evolutionary cycle is implemented once again.

Software implementation. The proposed GA to solve the fixed model has been implemented in the *Python* programming language (version 3.7.7) by making use of the *eaSimple* GA solver provided in the *DEAP* package (version 1.3) (Fortin et al., 2012). The software is written in such a way that the evaluation of the solution candidates can be carried out on several CPU cores in parallel. This allows for a significant reduction in computing time.

4.4.2 Flexible CEP models

As reviewed in Section 2.4.4, the literature presents two different ways to form flexible CEP models which are here referred to as the *empirical approach* and the *generative approach*. The empirical approach is concerned with determining the stochastically optimal parametrisation of a decision rule, whereas the generative approach is concerned with determining both the optimal structure of a decision rule and its optimal parametrisation. In this chapter, both approaches are used to create flexible CEP models for airport passenger terminal facilities. To this end, the following models are presented in this study: the *conditional-go decision rule model (CGDRM)* which is based on the empirical approach, and the *reward function decision rule model (RFDRM)* which is based on the generative approach.

4.4.2.1 Conditional-go decision rule model

A number of different conditional-go decision rule-based flexible CEP models for flexible engineering systems are discussed in the literature (Cardin & Hu, 2016; Cardin et al., 2015; Cardin, Xie et al., 2017; Cardin, Zhang et al., 2017; Hu et al., 2018; Xie et al., 2014; Zhao et al., 2018). The model presented in this study is an airport passenger terminal facility-specific adaptation of the flexible CEP model documented in Cardin and Hu (2016), Cardin et al. (2015) and Hu et al. (2018).

A conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ permits the creation of a scenario-specific capacity vector $\mathbf{K}_i^s$ for every scenario of uncertainty $\boldsymbol{\xi}^s \in \Omega$. Such a scenario-specific capacity vector $\mathbf{K}_i^s$ is created in an iterative process in which, starting at planning phase $t = 1$, the operational capacity $K_{i,t}^s$ of facility i in planning phase t and scenario s is defined with decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ based on (i) the parametrisation of the decision rule specified by parameter vector $\boldsymbol{\theta} = [\theta_1, \theta_2]$, (ii) the operational capacity $K_{i,t-1}^s$ available at the beginning of planning phase t and (iii) the history of the already disclosed uncertainty $\mathbf{d}_{i,[t]}^s$.

In this study, the GBM-based annual aggregated demand model is used to create scenarios of uncertain aggregated passenger demand $\boldsymbol{\xi}^s \in \Omega$. By means of the DHL demand model, annual aggregated demand is subsequently converted into DHL demand $\mathbf{d}_i$ of facility i. Therefore, the history of the already disclosed uncertainty in period t is expressed as DHL demand $\mathbf{d}_{i,[t]}^s = \left[d_{i,1}^s, d_{i,2}^s, \ldots, d_{i,t}^s\right]$. By making use of a conditional-go decision rule, operational capacity $K_{i,t}^s$ of facility i in planning phase t and scenario s can be formally expressed as

$$K_{i,t}^s = \mathcal{D}_{\boldsymbol{\theta}}\left(\mathbf{d}_{i,[t]}^s, K_{i,t-1}^s\right). \tag{4.28}$$

To decide how much capacity $K_{i,t}^s$ is provided in planning phase t and scenario s, the following process is applied within the conditional-go decision rule. In a first step, the throughput $\tau_{i,t-1}^s$ of the entire facility i at the beginning of planning phase t and scenario s is estimated as follows:

$$\tau^s_{i,t-1} = K^s_{i,t-1} \cdot \mu_{K,i} \tag{4.29}$$

where $K^s_{i,t-1}$ is the operational capacity at the beginning of planning phase t and $\mu_{K,i}$ is the average unit throughput of one unit of capacity of the facility i, e.g. the throughput of one single check-in desk or one security checkpoint line. Typically, unit throughput is expressed in the unit of passenger per hour. Then, the throughput surplus TS is estimated on the basis of the difference between the facility's throughput $\tau^s_{i,t-1}$ and the observed DHL demand $d^s_{i,t}$ of facility i in scenario s and planning phase t:

$$TS = \tau^s_{i,t-1} - d^s_{i,t}. \tag{4.30}$$

Given throughput surplus TS, the actual *if-then-else* operator is implemented. Here, the logical operator checks whether the throughput surplus TS of facility i is smaller than a threshold value, which is defined as θ_2 units of capacity times the unit throughput $\mu_{K,i}$:

$$TS < \theta_2 \cdot \mu_{K,i}. \tag{4.31}$$

If Statement 4.31 applies, the conditional-go decision rule adjusts the operational capacity of facility i in planning phase t to $K^s_{i,t} = K^s_{i,t-1} + \theta_1$ units. Otherwise, capacity is not adjusted in planning phase t. By repeating this decision process for every planning phase $t = 1, 2, \ldots, T$, a scenario-specific capacity vector $\mathbf{K}^s_i$ is determined by means of conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}}$.

Model formulation. The conditional-go decision rule is integrated into the deterministic counterpart of the stochastic CEP model presented in Equations 4.22 on page 113. The resulting flexible CEP model, which is referred to as the CGDRM in this study, is expressed as follows:

$$\underset{\boldsymbol{\theta}}{\arg\max} \quad \sum_{s=1}^{S} p_s \left(-\mathcal{C}_{i,0}(\Delta K_{i,0}, \Delta A_{i,0}) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_{i,t}(d_{i,t}^s, K_{i,t}^s) - \mathcal{C}_{i,t}(d_{i,t}^s, K_{i,t}^s) \right) \right) \tag{4.32a}$$

$$\text{s.t.} \quad K_{i,t}^s = \mathcal{D}_{\boldsymbol{\theta}} \left(\mathbf{d}_{i,[t]}^s, K_{i,t-1}^s \right), \tag{4.32b}$$

$$\boldsymbol{\xi}^s \in \Omega, \tag{4.32c}$$

$$d_{i,t}^s = f(\xi_t^s, t, PAXATM_t, \mu_R, \hat{r}_i), \tag{4.32d}$$

$$\mathbf{d}_{i,[t]}^s = \left[d_{i,1}^s, d_{i,2}^s, \ldots, d_{i,t}^s \right], \tag{4.32e}$$

$$K_{i,t}^s \in \mathbb{N}_0, \tag{4.32f}$$

$$-\Delta K_i^{max} \leq \Delta K_{i,t}^s \leq \Delta K_i^{max}, \tag{4.32g}$$

$$p_1 = p_2 = \ldots = p_S, \tag{4.32h}$$

$$0 \leq p_s \leq 1, \tag{4.32i}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{4.32j}$$

The objective of the CGDRM is to determine the stochastically optimal parameter vector $\boldsymbol{\theta}^*$ for conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ in such a way that the ENPV of airport passenger terminal facility i is maximized over the entire planning period of an ASP project. The conditional-go decision rule is defined in Constraint 4.32b. The history of the disclosed uncertainty is specified in Constraint 4.32e. The remaining constraints of the CGDRM are identical with the fixed model, see Equations 4.24 on page 116.

The size of the solution space of the CGDRM is defined by parameters θ_1 and θ_2. As mentioned above, both θ_1 and θ_2 refer to a number of units of capacity for facility i. Consequently, both elements of the parameter vector must be integers. To further restrict the solution space of the CGDRM, it is assumed that, in accordance with Constraint 4.32g, θ_1 and θ_2, are limited to the following set

$$\theta_1, \theta_2 \in \{-\Delta K_i^{max}, -\Delta K_i^{max} + 1, \ldots, \Delta K_i^{max}\} \tag{4.33}$$

which has a cardinality of $2\Delta K_i^{max}+1$. Consequently, given the fact that the parameter vector $\boldsymbol{\theta}$ consists of 2 elements which can both take on $2\Delta K_i^{max}+1$ different values, $(2\Delta K_i^{max}+1)^2$ feasible solution candidates for the CGDRM exist. For instance, if ΔK_i^{max} is set to 50 units, 101^2 feasible solution candidates exist.

Theoretically, both the enumeration method used for the baseline model, as well as the GA could be applied to near-optimally solve the CGDRM. However, especially for large values of K_i^{max}, the enumeration method would involve very long computing times, which should be avoided as far as possible for practical reasons. Since a GA-based solution procedure has already been used for the fixed model, it was decided to solve the CGDRM by means of a GA as well. This provides planners with a robust solution procedure that can efficiently find a solution for the CGDRM, even in the case of relatively large values for ΔK_i^{max}.

Proposed solution procedure. The GA-based solution procedure proposed for the CGDRM is largely identical to the solution procedure of the fixed model, see Figure 4.9 on page 119 and Algorithm 2. For this reason, only the differences between the two implementations are discussed in more detail in this section.

Genetic representation. Feasible solution candidates of the CGDRM are parameter vectors $\boldsymbol{\theta}$ whose elements are integers which are further restricted to the set specified in Equation 4.33. The phenotypes are encoded into chromosomes $\mathbf{x}$ with Equation 4.34. The same function is used to decode chromosomes $\mathbf{x}$ into parameter vectors $\boldsymbol{\theta}$:

$$\mathbf{x} = \boldsymbol{\theta} = [\theta_1, \theta_2]\,. \tag{4.34}$$

Generation of initial population. The initial population of chromosomes $P(0)$ of the CGDRM is randomly generated. To do this, the genes of all chromosomes generated in this process are assigned a randomly selected value from the set of feasible values for θ_1 and θ_2 defined in Equation 4.33. Each element of this set has the same probability being selected in this process.

Evolutionary cycle. By means of Algorithm 3, all the chromosomes $(\mathbf{x}_{1,g},\dots,\mathbf{x}_{M,g})$ of the current population $P(g)$ are evaluated for their fitness. Algorithm 3 must be provided with DHL scenarios $\mathbf{d}_i^1,\mathbf{d}_i^2,\dots,\mathbf{d}_i^S$ for facility i, which are created[17] before the GA is executed. For the evaluation of all the populations of chromosomes, the same set of demand scenarios is used.

Algorithm 3 Evaluation in CGDRM

procedure EVALUATECGDRM$(P(g),\mathbf{d}_i^1,\mathbf{d}_i^2,\dots,\mathbf{d}_i^S)$
  Initialise $\mu_{K,i}$ ▷ Get unit throughput of facility i
  Initialise $K_{i,0}$ ▷ Get the initially installed capacity
  for $\mathbf{x}_{m,g} \in P(g)$ **do** ▷ Loop over all chromosomes of population $P(g)$
    $\boldsymbol{\theta}_{m,g} = \left[\theta_{1,m,g},\theta_{2,m,g}\right] \leftarrow f(\mathbf{x}_{m,g})$ ▷ Decode chromosome to get $\boldsymbol{\theta}_{m,g}$
    for $s = 1$ to S **do** ▷ Loop over all scenarios s
      $TS \leftarrow 0$
      $K_{i,0}^s \leftarrow K_{i,0}$ ▷ Set initially operational capacity
      for $t = 1$ to T **do** ▷ Loop over all planning phases t to create $\mathbf{K}_i^s$
        $\tau_{i,t-1}^s \leftarrow K_{i,t-1}^s \cdot \mu_{K,i}$ ▷ Facility throughput in phase $t-1$
        $TS \leftarrow \tau_{i,t-1}^s - d_{i,t}^s$ ▷ Throughput surplus
        if $TS < \theta_2 \cdot \mu_{K,i}$ **then** ▷ *If* statement
          $K_{i,t}^s \leftarrow K_{i,t-1}^s + \theta_1$ ▷ *Then* statement
        else
          $K_{i,t}^s \leftarrow K_{i,t-1}^s$ ▷ *Else* statement
        end if
      end for
      $NPV_{m,g}^s \leftarrow NPV\left(\mathbf{K}_i^s,\mathbf{d}_i^s\right)$ ▷ Get NPV of scenario s and rule $\mathcal{D}_{\boldsymbol{\theta}_{m,g}}$
    end for
    $ENPV_{m,g} \leftarrow \mathbb{E}\left[NPV_{m,g}^1,\dots,NPV_{m,g}^S\right]$ ▷ Get fitness of $\mathbf{x}_{m,g}$
  end for
  return $(ENPV_{1,g},\dots,ENPV_{M,g})$ ▷ Return fitness values of population $P(g)$
end procedure

To evaluate a chromosome $\mathbf{x}_{m,g} \in P(g)$ for its fitness, it is first decoded by means of Equation 4.34 in order to get parameter vector $\boldsymbol{\theta}_{m,g} = \left[\theta_{1,m,g},\theta_{2,m,g}\right]$. Then, a scenario-specific capacity vector $\mathbf{K}_i^s$ is created by means of the conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}_{m,g}}$. Here, the logical *if-then-else* operator specified in Equations 4.28 to 4.31 is applied. Given $\mathbf{K}_i^s$ and $\mathbf{d}_i^s$, the resulting $NPV_{m,g}^s$ of facility i for scenario s and decision rule $\mathcal{D}_{\boldsymbol{\theta}_{m,g}}$ can be computed. By repeating this process for all scenarios $s = 1,2,\dots,S$, the NPV of every

[17] DHL demand scenarios are created with the annual aggregated demand model introduced in Section 4.1 and the DHL model presented in Section 4.2 before the GA is executed.

scenario given by decision rule $\mathcal{D}_{\boldsymbol{\theta}_{m,g}}$ is determined accordingly. Subsequently, by calculating the arithmetic mean of all the scenario-specific NPVs, the $ENPV_{m,g}$ over all the scenarios, which is used as the fitness value of chromosome $\mathbf{x}_{m,g}$, is derived.

Once all the chromosomes of the current population $P(g)$ have been evaluated for their fitness, an offspring population $P(g+1)$ is generated by means of genetic operators. In this way, the CGDRM uses almost the same genetic operators as the fixed model. Chromosomes are selected with *tournament selection* of tournament size 4. In addition, elitism, analogous to the fixed model, is applied. Crossover is implemented with the *one point crossover* method in which the genetic information of two parental chromosomes is exchanged in order to form two child chromosomes (Bäck et al., 2018). Finally, the *uniform mutation operator* is applied to replace the values of some genes of some chromosomes with a randomly selected value from the set specified in Equation 4.33.

Termination condition(s). The evolutionary cycle is repeated until the maximum number of generations G, which is a parameter of the CGDRM, has been reached. The best performing chromosome of population $P(G)$ is subsequently selected as as the near-optimal solution $\boldsymbol{\theta}^* = [\theta_1^*, \theta_2^*]$ of the CGDRM.

Software implementation. The proposed GA to solve the CGDRM has been implemented in the *Python* programming language (version 3.7.7) by making use of the *eaSimple* GA solver provided in the DEAP package (version 1.3) (Fortin et al., 2012). The software is written in such a way that the evaluation of the solution candidates can be carried out on several CPU cores in parallel. This allows for a reduction in computing time.

4.4.2.2 Reward function decision rule model

The second flexible CEP model presented in this study is based on the *generative approach*, in which both the optimal structure of a decision rule as well its optimal parametrisation are determined. The generative approach-based CEP model for airport passenger terminal facilities presented in this study is an adaptation of the the works of Hu et al.

(2020) and Hu and Guo (2019), who designed their model for a waste-to-energy plant in Singapore. Instead of using a conditional-go decision rule $\mathcal{D}$, Hu et al. (2020) and Hu and Guo (2019) employ a non-linear decision rule $\mathcal{L}$, see Section 2.4.4.2, which they refer to as a *reward function*, in order to inform DMs on how to optimally adjust the capacity of an engineering system. For this reason, this flexible CEP model is called the *reward function decision rule model (RFDRM)*. In the following, the mode of operation of the RFDRM is explained in more detail.

For each scenario of uncertainty $\boldsymbol{\xi}^s \in \Omega$ generated with the annual aggregated demand model presented in Section 4.1 and the DHL model introduced in Section 4.2 as well as for every planning phase $t = 1, 2, \ldots, T$, DMs determine the operational capacity of airport passenger terminal facility i with the reward function $\mathcal{L}$. In this process, the reward function $\mathcal{L}$ decides whether and how the operational capacity of facility i should be adjusted, i.e. expanded or contracted. For all of these adjustment decisions, DMs can choose from a finite set of adjustment options $e = \{e_1, e_2, \ldots, e_{n_e}\}$. Set e must be defined in advance and contains all capacity adjustments which are considered feasible by the airport planners. For instance, airport planners could define that capacity can be adjusted by $e = \{-1, 0, 1, 2, 5\}$ units of capacity. All other capacity adjustment options, e.g. an adjustment by 4 units, are considered infeasible and can therefore not be implemented. Consequently, capacity $K^s_{i,t}$ of facility i in scenario s and planning phase t can be written as

$$K^s_{i,t} = K^s_{i,t-1} + e_l \,, \qquad e_l \in \{e_1, e_2, \ldots, e_{n_e}\} \tag{4.35}$$

where $K^s_{i,t-1}$ is the operational capacity at the beginning of planning phase t in scenario s and n_e specifies the number of adjustment options defined in set e. To determine which adjustment option $e_l \in e$ should be implemented in planning phase t and scenario s, reward function $\mathcal{L}$ is used to assign a *priority index* $\lambda^s_{l,t}$ to each member of the set e (Hu et al., 2020). In order to do so, the features V_l of option $e_l \in e$ are considered. According to Hu and Guo (2019), features are objective descriptors of option e_l, such as the investment costs associated with e_l. In line with the works of Hu et al. (2020) and Hu and Guo (2019), the following features of options $e_l \in e$ are considered in this study: (i) the capacity adjustment itself, which is denoted as e_l, (ii) the operational capacity $K^s_{i,t-1}$ at the beginning of planning phase t in scenario s, (iii) the installation costs $CI(e_l)$ associated with option e_l and (iv) the disclosed uncertainty $\xi^s_{i,t}$ in planning phase t of scenario s, which is expressed in terms of the disclosed DHL demand $d^s_{i,t}$. Hu and Guo (2019) also consider the available resources, i.e. the maximum permissible capacity of facility i, as a fifth feature. However, for this study it was decided not to use the available resources as a feature, since maximum capacity is somehow controlled through the elements of set e, see Equation 4.35[18].

Thus, for every scenario s and planning phase t, the priority index $\lambda^s_{l,t}$ of option $e_l \in e$ is calculated as follows:

$$\lambda^s_{l,t} = \mathcal{L}\left(\mathbf{d}^s_{i,[t]}, V_l\right), \quad V_l = \{e_l, K^s_{i,t-1}, CI(e_l), d^s_{i,t}\} \tag{4.36}$$

where $\mathbf{d}^s_{i,[t]}$ refers to the history of the disclosed DHL demand for facility i in planning phase t and scenario s. The option $e^{s,*}_{l,t}$ which results in the highest reward function value $\lambda^s_{l,t}$ for all $e_l \in e$ in planning phase t and scenario s is subsequently chosen for implementation. Hence, the operational capacity $K^s_{i,t}$ of facility i is expressed as

$$K^s_{i,t} = K^s_{i,t-1} + e^{s,*}_{l,t} = K^s_{i,t-1} + \arg\max_{e_l \in e}\left(\lambda^s_{l,t}\right) \tag{4.37}$$

where $\arg\max_{e_l \in e}\left(\lambda^s_{l,t}\right)$ refers to the adjustment option $e_l \in e$ which leads to the highest priority index. By iteratively repeating this selection process for all planning phases $t = 1, 2, \ldots, T$, a capacity vector $\mathbf{K}^s_i$ for scenario s is created.

[18]Since the number of planning phases is finite, the maximum possible capacity is given as $K^{max}_i = K_{i,0} + \max(e) \cdot T$, while the minimum capacity is given as $K^{min}_i = K_{i,0} - \min(e) \cdot T$. The largest and the smallest element of e are indicated with $\max(e)$ and $\min(e)$, respectively.

Model formulation. The actual form, structure, and parametrisation of the non-linear decision rule $\mathcal{L}$ presented in Equation 4.36 has intentionally not been specified. Indeed, the objective of the RFDRM is to determine the stochastically optimal structure and parametrisation of reward function $\mathcal{L}$ in such a way that the ENPV of passenger terminal facility i is maximized over all scenarios of uncertainty $\boldsymbol{\xi}^s \in \Omega$. Following Hu and Guo (2019) and Hu et al. (2020), the deterministic counterpart of the stochastic CEP model presented in Equations 4.22 on page 113 is subsequently extended as follows in order to integrate reward function $\mathcal{L}$:

$$\underset{\mathcal{L}}{\arg\max} \quad \sum_{s=1}^{S} p_s \left(-\mathcal{C}_{i,0}(\Delta K_{i,0}, \Delta A_{i,0}) + \sum_{t=1}^{T} \frac{1}{(1+\delta)^t} \left(\mathcal{R}_{i,t}(d^s_{i,t}, K^s_{i,t}) - \mathcal{C}_{i,t}(d^s_{i,t}, K^s_{i,t}) \right) \right) \tag{4.38a}$$

$$\text{s.t.} \quad K^s_{i,t} = K^s_{i,t-1} + \underset{e_l \in \{e_1,\ldots,e_{n_e}\}}{\arg\max} \left(\lambda^s_{l,t} \right), \tag{4.38b}$$

$$\lambda^s_{l,t} = \mathcal{L}\left(\mathbf{d}^s_{i,[t]}, V_l \right), \tag{4.38c}$$

$$V_l \in \{e_l, K^s_{i,t-1}, CI(e_l), d^s_{i,t}\}, \tag{4.38d}$$

$$\boldsymbol{\xi}^s \in \Omega, \tag{4.38e}$$

$$d^s_{i,t} = f(\xi^s_t, t, PAXATM_t, \mu_R, \hat{r}_i), \tag{4.38f}$$

$$\mathbf{d}^s_{i,[t]} = \left[d^s_{i,1}, d^s_{i,2}, \ldots, d^s_{i,t} \right], \tag{4.38g}$$

$$K^s_{i,t} \in \mathbb{N}_0, \tag{4.38h}$$

$$p_1 = p_2 = \ldots = p_S, \tag{4.38i}$$

$$0 \leq p_s \leq 1, \tag{4.38j}$$

$$\sum_{s=1}^{S} p_s = 1 \tag{4.38k}$$

where Constraints 4.38b, 4.38c and 4.38d integrate reward function $\mathcal{L}$ in the RFDRM.

Proposed solution procedure. In line with Hu et al. (2020) and Hu and Guo (2019), *gene expression programming (GEP)* algorithm is applied in this study to determine the optimal structure and parametrisation of the reward function $\mathcal{L}$. GEP is an evolutionary optimization algorithm, similar to the GA, which is however capable of evolving computer programs, i.e. mathematical formulae, logical rules, etc. (Ferreira, 2001). Hereafter, the proposed solution procedure is presented in more detail. In a first step, the genotypes and phenotypes used in the proposed GEP approach are explained. Further, the generation of an initial population, as well as the evolutionary cycle is described.

Genetic representation. According to Ferreira (2006) and Zhong et al. (2017), the solution candidates used in GEP are computer programs which are encoded by means of fixed-length chromosomes $\mathbf{x}$. Each of these chromosomes have two distinctive parts: a *head* and a *tail*. While the head of a chromosome consists of genes which are either so-called *functions* or *terminals*, the genes of the tail are formed entirely of *terminals*. As the name implies, *functions* are mathematical functions such as the addition or subtraction operators. *Terminals*, on the other hand, can either be input variables or constants. Functions and terminals that the GEP algorithm may use must be defined in a respective set. The set of all functions Ψ defines which mathematical functions are permitted to be used in the solution candidates. Following Hu et al. (2020) and Hu and Guo (2019), set Ψ applied in this study contains the following mathematical operators: addition, subtraction, multiplication and protected division. This protected division is a modified division operator which yields to zero in case of a division by zero (Hu et al., 2020).

$$\Psi = \{\mathrm{ADD}, \mathrm{SUB}, \mathrm{MUL}, \mathrm{PDIV}\} \tag{4.39}$$

Valid input variables are specified in the set of terminals Γ, which, for the application proposed in this study, consists of all elements in set V_l

$$\Gamma = V_l = \{e_l, K^s_{i,t-1}, CI(e_l), d^s_{i,t}\}. \tag{4.40}$$

Chromosomes **x** are decoded into computer programs by means of the *width-first search scheme*, where the computer program is expressed in terms of an *expression tree* (Zhong et al., 2017). To explain the decoding method, the following chromosome is considered as an example:

$$\mathbf{x} = \left[\underbrace{\text{ADD}, \text{MUL}, \text{PDIV}, \text{SUB}, d^s_{i,t}, \text{MUL}}_{\text{Head}}, \underbrace{e_l, K^s_{i,t-1}, d^s_{i,t}, d^s_{i,t}, CI_t, CI_t, e_l}_{\text{Tail}} \right]. \tag{4.41}$$

The first gene of the head, which, in the example presented in Equation 4.41, is the addition operator, is expanded as the first node of the expression tree, see Figure 4.10. Then, this first node is further expanded into u sub-nodes, where u refers to the maximum *arity* of the functions defined in Ψ. The term arity refers to the number of arguments the functions defined in Ψ take. In this study, the maximum arity is set to $u = 2$. Consequently, the two child nodes of the addition operator are expanded by considering genes 2 and 3 of the example chromosome. As illustrated in Figure 4.10, these genes contain the multiplication and the protected division operator. Then, the procedure of expanding nodes is repeated for all the genes located in the head of the chromosome. Once the head has been completely expanded, the elements of the tail are assigned from left to right to all still empty children nodes of the expression tree. Since terminals act as the *leaves* of the expression tree, they cannot be further expanded. It is possible that some genes in the tail of the chromosome are not assigned to a leave and therefore remain unused. The decoding process is finished when the expression tree has no more empty leaves and therefore cannot be expanded further. Consequently, chromosome **x** has been transformed into a corresponding expression tree which describes both the structure and parametrisation of reward function $\mathcal{L}$. For instance, the example chromosome presented in Equation 4.41 can be transformed into the following reward function:

$$\mathcal{L} = K^s_{i,t-1} d^s_{i,t} - (d^s_{i,t})^2 + \frac{d^s_{i,t} CI_t(e_l)}{e_l}. \tag{4.42}$$

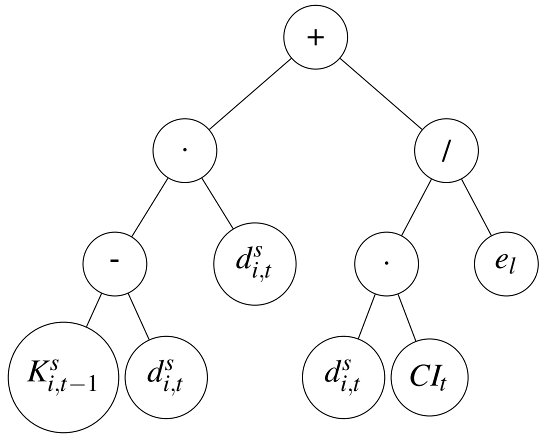

Figure 4.10: Expression tree relating to the chromosome defined in Equation 4.41.

In order to ensure that a valid expression-tree can be generated from each chromosome, Ferreira (2006) stipulated that the length of the head and the length of the tail of the chromosomes must be fixed. Given the maximum arity u of the functions, the number of genes in the head n_{Head} and the number of genes in the tail n_{Tail} of a chromosome are related to each other as follows (Ferreira, 2006):

$$n_{\text{Tail}} = n_{\text{Head}} \cdot (u-1) + 1. \tag{4.43}$$

At this point, it is important to mention that for the application proposed in this study only a decoding function is needed. There is no need to encode expression trees into chromosomes.

Generation of initial population. Similar to the GA-based approaches used for the fixed model and the CGDRM, an initial population $P(0)$ of chromosomes must be generated on a random basis for the GEP algorithm-based solution approach which is used for the RFDRM as well. In a first step, the length of the chromosomes is to be defined. In line with Hu and Guo (2019), the length of the head of the chromosomes has been set to $n_{\text{Head}} = 8$ genes. Then, with a maximum arity of $u = 2$, the length of the tail of the chromosomes is determined with Equation 4.43 as $n_{\text{Tail}} = 8 \cdot (2-1) + 1 = 9$ genes. This leads to fixed-length chromosomes which contain $n_{\text{Head}} + n_{\text{Tail}} = 17$ genes. In a second step, M chromosomes are generated randomly, where the values of the genes located in the heads of the chromosomes are sampled with uniform probability from sets Γ and Ψ, while for the tail the values of the genes are randomly sampled from the set of terminals Γ only.

Evolutionary cycle. Before starting the evolutionary cycle of the GEP algorithm, which to a large extent is identical with evolutionary cycle of the GA, all scenarios of uncertainty $\boldsymbol{\xi}^s \in \Omega$ are generated by means of the aggregated annual demand model defined in Section 4.1 and the DHL model introduced in Section 4.2. These scenarios remain unchanged for the entire evolutionary cycle, and once these scenarios are given, the actual evolutionary cycle is initiated.

All the chromosomes $\mathbf{x}_{m,g}$ of the current population $P(g)$ are evaluated for their fitness with Algorithm 4. To this end, each chromosome $\mathbf{x}_{m,g}$ is first decoded into a corresponding reward function $\mathcal{L}_{m,g}$ by means of the *width-first search scheme* introduced above. Next, using the resulting reward function $\mathcal{L}_{m,g}$, a capacity vector $\mathbf{K}_i^s$ is created for every scenario of uncertainty, where the procedure explained in Equations 4.36 and 4.37 is applied. Given $\mathbf{K}_i^s$ and $\mathbf{d}_i^s$, the resulting $\text{NPV}_{m,g}^s$ of facility i for scenario s is calculated. By repeating this process for all scenarios $s = 1, \ldots, S$, the NPV of every scenario is calculated with the decision rule $\mathcal{L} = f(\mathbf{x}_{m,g})$ accordingly. Subsequently, by calculating the arithmetic mean of all scenario-specific $\text{NPV}_{m,g}^s$, the ENPV over all the scenarios, which is $\text{ENPV}_{m,g}$, is used to express the fitness of chromosome $\mathbf{x}_{m,g}$.

Once all the chromosomes of the current population $P(g)$ have been evaluated for their fitness, an offspring population $P(g+1)$ is generated by means of genetic operators. In contrast to the GA, GEP uses four different genetic operators, namely (i) selection, (ii) crossover, (iii) mutation and (iv) transposition.

- *Selection.* Similar to the GA used for the fixed model and the CGDRM, *tournament selection* with a tournament size of 4 is used to form population $P'(g)$. Additionally, with the help of *elitism*, the best performing chromosome of population $P(g)$ is directly copied into the offspring population $P(g+1)$.

- *Crossover.* According to Zhong et al. (2017), a combination of both *one-point* and

Algorithm 4 Evaluation in RFDRM

procedure EVALUATERFDRM($P(g), \mathbf{d}_i^1, \mathbf{d}_i^2, \dots, \mathbf{d}_i^S$)
  Initialise $K_{i,0}$ ▷ Get initial capacity of facility i
  Initialise $e \leftarrow \{e_1, e_2, \dots, e_{n_e}\}$ ▷ Define set of adjustment options
  for $\mathbf{x}_{m,g} \in P(g)$ **do** ▷ Loop over all chromosomes of population $P(g)$
    $\mathcal{L}_{m,g} = f(\mathbf{x}_{m,g})$ ▷ Decode chromosome to get reward function
    for $s = 1$ to S **do** ▷ Loop over all scenarios s
      $K_{i,0}^s \leftarrow K_{i,0}$ ▷ Set initially operational capacity
      for $t = 1$ to T **do** ▷ Loop over all planning phases t to create $\mathbf{K}_i^s$
        for $e_l \in e$ **do** ▷ Loop over adjustment options e_l
          $V_l \leftarrow \{e_l, K_{i,t-1}^s, CI(e_l), d_{i,t}^s\}$ ▷ Populate set V_l
          $\lambda_{l,t}^s \leftarrow \mathcal{L}_{m,g}\left(\mathbf{d}_{i,[t]}^s, V_l\right)$ ▷ Calculate priority index for e_l
        end for
        $K_{i,t}^s \leftarrow K_{i,t-1}^s + \arg\max_{e_l \in e}\left(\lambda_{l,t}^s\right)$ ▷ Select e_l with highest $\lambda_{l,t}^s$ value
      end for
      $NPV_{m,g}^s \leftarrow NPV(\mathbf{K}_i^s, \mathbf{d}_i^s)$ ▷ Get NPV of scenario s and rule $\mathcal{L} = f(\mathbf{x}_{m,g})$
    end for
    $ENPV_{m,g} \leftarrow \mathbb{E}\left[NPV_{m,g}^1, \dots, NPV_{m,g}^S\right]$ ▷ Get fitness of $\mathbf{x}_{m,g}$
  end for
  return $(ENPV_{1,g}, \dots, ENPV_{M,g})$ ▷ Return fitness values of population $P(g)$
end procedure

two-point crossover is applied to combine the genetic information of two parental chromosomes of population $P'(g)$ at random in order to form population $P''(g)$.

- *Mutation.* Chromosomes in the population $P''(g)$ are subject to uniform mutation with a probability of p_M in order to form population $P'''(g)$. The mutation operator used for GEP ensures that elements of a chromosome head can only be mutated into other feasible values for terminals and functions as defined in sets Γ and Ψ, while elements in the chromosome tail must only be allowed to randomly take values as defined in set Γ.

- *Transposition.* Transposition is a genetic operator applied specifically in GEP algorithms when it randomly moves fragments of a chromosomes to other positions within the same chromosome. With transposition, population $P''''(g)$ is generated. As suggested by Ferreira (2001, 2006) and Zhong et al. (2017), two different types of transposition operators are applied in this study: *IS transposition*[19] and *RIS transposition*[20] (Ferreira, 2001, 2006; Zhong et al., 2017). The *gene transposition operator*, which is applied to solution candidates consisting of more than one chromosome, is not applied in this study, since solution candidates of the RFDRM consist only of one single chromosome.

Termination condition(s). After successfully applying all the genetic operators mentioned above, offspring population $P(g+1)$ is created as $P(g+1) = P''''(g)$. As is the case for the fixed model and the CGDRM, the evolutionary cycle of the RFDRM is terminated as soon as the maximum number of generations G has been reached. Subsequently, the best performing chromosome of population $P(G)$ is considered the near-optimal solution of the RFDRM. If the termination conditions are not met, the entire evolutionary cycle of the GEP algorithm is executed once again.

Software implementation. The proposed GEP algorithm to solve the RFDRM has been implemented in the *Python* programming language (version 3.7.7) by making use of the *gep_simple* GEP solver provided in the *GEPPY* package (version 0.1.2) (Gao, 2018). The software is written in such a way that the evaluation of the solution candidates can be carried out on several CPU cores in parallel. This allows for a reduction in computing time.

[19]IS transposition refers to *insertion sequence* transposition, which is responsible for moving small snippets of a chromosome to a random position within the head of the same chromosome.

[20]RIS transposition refers to *root insertion sequence*, which is responsible for moving small segments of the head of a chromosome to the beginning of the head of the chromosome.

Chapter 5

Planning example

In this chapter, the strategic capacity planning framework presented in Section 4 is applied in a real-world strategic planning example to determine facility requirements for existing check-in facilities at ZRH Airport. To simplify matters, this planning example focuses exclusively on the check-in facilities at ZRH Airport. However, it is important to note that the strategic capacity planning framework proposed in this study can be applied without loss of generality both to other airport passenger terminal facilities at ZRH Airport, such as security checkpoints or baggage carousels, as well as at other airports.

Following the general structure of the capacity planning framework proposed in Section 4, this planning example consists of two main parts: (i) the generation of demand scenarios and (ii) the determination and comparison of optimal facility requirements for a number for system designs, i.e. candidate flexibilities, for existing check-in facilities at ZRH Airport by means of conventional and flexible CEP models. The chapter is organised as follows: Section 5.1 presents and summarises the planning principles underlying this example. ZRH Airport and the check-in facility for which facility requirements are determined are briefly introduced. There follows an explanation of which sources of uncertainty and candidate flexibilities are taken into account, and how facility requirements that were created with different CEP models are compared by means of their *value of flexibility (VoF)*. Section 5.2 presents the inventory of the check-in facilities considered and the parametrisation of the models used in the course of this planning example. Subsequently, annual aggregated passenger demand scenarios for ZRH Airport and DHL demand scenarios for the check-in facility in focus are calculated and presented in Section 5.3. In Section 5.4, conventional and flexible facility requirements for a total of three different candidate flexibilities for check-in facilities at ZRH Airport are determined by means of the fixed model, the CGDRM and the RFDRM. Following this, the facility requirements generated in this process are compared with each other with the help of the baseline model results. Further, the facility requirements created with the fixed model, the CGDRM and the RFDRM, are examined for their sensitivity to changes in input and parameters. Finally, Section 5.5 discusses the observed solution performance of the CEP models presented.

5.1 Planning principles

5.1.1 System description

ZRH is Switzerland's largest airport. In 2019, 77 airlines provided flight connections to 138 European and 65 intercontinental destinations (Flughafen Zürich AG [FZAG], 2020). Also, ZRH handled 31.5 million passengers in 2019, making it the 72^{nd} largest aerodrome in the world (ACI, 2020b). To meet this traffic volume, ZRH Airport has two terminals, *Terminal 1* and *Terminal 2*. *Terminal 1* is predominantly used by *Swiss International Airlines* and its *Star Alliance* partners, while the remaining traffic is handled in *Terminal 2*.

Most airport passenger terminal facilities at ZRH Airport, such as the security checkpoints, the immigration facilities or the emigration facilities, are operated as *common-use* facilities. Check-in facilities, however, are an exception due to the fact that a majority of the check-in desks are dedicated to airlines, airline alliances or handling agents. In fact, hub carrier *Swiss International Airlines* and its *Star Alliance* partner airlines use two dedicated check-in facilities almost exclusively: *Check-in 1* located in *Terminal 1* and

Check-in 3 situated next to the airport's railway station in *Terminal 2*, see Figure 5.1.

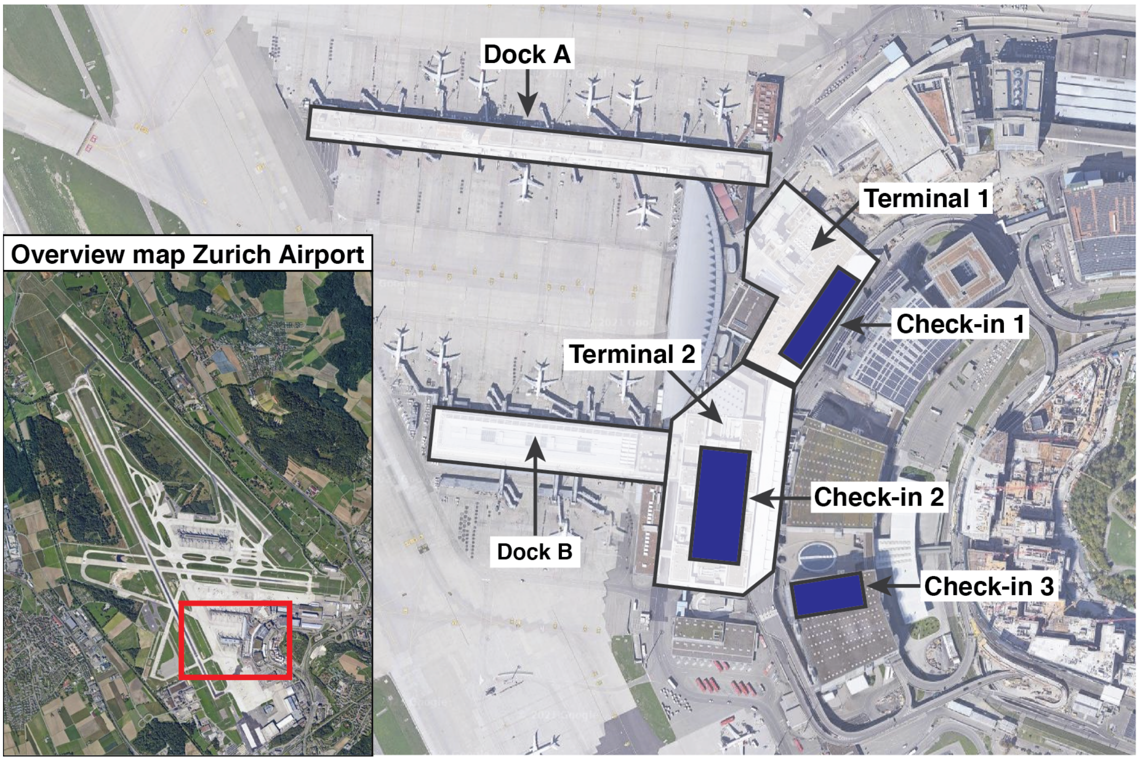

Figure 5.1: General map of ZRH Airport showing the location of *Terminals 1 and 2* and *Check-in 1, 2 and 3*. Note: The map was created by the author based on aerial photographs of ZRH Airport obtained through https://www.google.com/maps/.

For this planning example, it is assumed that *Check-in 1* as well as *Check-in 3* are located in the same building and that the joint facility requirements for both facilities are determined. Thus, the term *Check-in 1 and 3*, which refers to the combined facility requirements, is used for the remainder of this planning example. In practice, airport planners often create such combined facility requirements, as this can simplify the creation of planning *alternatives*; these describe how facility requirements can actually be implemented at an airport, see Section 2.1.1. It should be noted that in Chapter 4, the subscript i is used to refer to a generic passenger terminal facility, whereas in this chapter subscript i is replaced with CH whenever *Check-in 1 and 3* is explicitly referred to.

5.1.2 Sources of uncertainty

ASP is subject to uncertainty from a number of different sources, as reviewed in Section 2.3.2. For this planning example, it was decided to further consider two specific sources of uncertainty, namely (i) uncertainty in demand and (ii) uncertainty in the service rate of check-in facilities.

Uncertainty in demand can be rather significant, especially when long planning horizons are considered. As mentioned in Section 2.1, Maldonado (1990) reports forecast errors in the range of 34 % to 210 % for demand outlooks covering 15 years. For this reason, the importance of demand uncertainty is highlighted in guidance material for airport planners (IATA, 2017; Kennon et al., 2013; Kincaid et al., 2012; Landrum & Brown et al., 2010), also in the scientific literature on strategic airport planning (Burghouwt, 2007; De Neufville et al., 2013), as well as in the literature on CEP models (Freidenfelds, 1981; Geng & Jiang, 2009; Julka et al., 2007; Luss, 1982; Martínez-Costa et al., 2014; Van Mieghem, 2003; Wu et al., 2005). Annual aggregated passenger demand scenarios are generated for this planning example by means of the GBM-based annual aggregated demand model introduced in Section 4.1. These annual aggregated demand scenarios are subsequently converted into DHL demand scenarios for *Check-in 1 and 3* with the unsaturated DHL model and the saturated DHL model introduced in Section 4.2.

The second source of uncertainty selected for further consideration is the average process or service rate of check-in facilities. This service rate describes how many passengers are handled on average per time unit, e.g. per hour, by an airport passenger terminal facility. Here, both procedural and technological factors may potentially affect the average service rate of a check-in facility (Ashford et al., 2013; IATA, 2017). Procedural factors consider, for instance, the introduction of new safety-related measures, which could slow down the check-in process. On the other hand, technological advances, such as web-based check-in[21], have the potential to increase the average throughput of a check-in desk.

In this study, the influence of uncertainty, here in the average service rate $\mu_{K,CH}$ of check-in desks, on optimal facility requirements created with CEP models is not examined by means of scenarios of uncertainty $\xi^s \in \Omega$, but rather by means of sensitivity analyses. The reason for this decision lies in the fact that the literature on the creation of scenarios of uncertainty for the service rate of check-in desks is, at best, limited. Regarding the modelling of the uncertain influence of procedural aspects on the service rate of check-in desks, there is, to the best of the author's knowledge, no scientific literature available. As to technological factors, a large body of literature on technological innovation diffusion is available (Meade & Islam, 2006). To model technological change and innovation, various methods, such as agent-based models (Dawid, 2006), logistic models (Grübler et al., 1999) or "scenario analysis, portfolio theory, and multi-criteria optimization" (Grübler & Fuss, 2012, p. 10) are proposed in the literature. For example, Halpern et al. (2021) discuss the effects of the digital transformation on airports, while Ueda and Kurahashi (2014) present an agent-based model that examines the adoption of self-service technology at check-in. Unfortunately, however, the literature, in applying these methods to airport processes, does not focus on methods which allow the generation of scenarios of uncertainty applicable in the context of this study.

5.1.3 Candidate flexibilities

Candidate flexibilities describe flexible system designs based on real options *on* systems and/or real options *in* systems. Airport passenger terminal-related implementations of real options presented in the literature have been reviewed in Section 2.2.2. Based on this review, three candidate flexibilities were selected that are suitable for application

[21] As pointed out by IATA (2017), the check-in process is in the midst of a fundamental transformation which is largely driven by the advance of the Internet-based technology. While in the past passengers conducted their entire check-in process on site, web-based technology will offer airports and handling agents the possibility of outsourcing large parts of the check-in process to Internet-based services (Lu et al., 2011). Further, Wilson (2019) expects that in future an ever-increasing segment of passengers will not require classical check-in infrastructure at airports any longer. Instead, it is expected that passengers will predominantly use self-service infrastructure by means of mobile devices.

on *Check-in 1 and 3*. These candidate flexibilities, which are hereafter referred to as *Evaluation 1*, *Evaluation 2* and *Evaluation 3*, are defined as follows:

(i) *Evaluation 1* deals with the implementation of real options *on* systems in *Check-in 1 and 3*. Of the generic real options strategies reviewed in Section 2.2.2, only a subset is applicable to airport passenger terminal facilities[22]. It was therefore decided to examine whether and how the future development of *Check-in 1 and 3* can be made flexible with the *option to defer* and the *option to alter the operating scale*. For this reason, it is assumed that systems which are equipped with the *option to alter the scale* inherently include the *options to expand* and *to contract*, as this is considered the basic functionality of this option.

(ii) *Evaluation 2* is an extension of *Evaluation 1*. Given the basic flexibilities introduced in *Evaluation 1*, i.e. the *option to defer* and the *option to alter* the scale, the possibility of developing *Check-in 1 and 3* in a modular way is analysed. Modularisation, as introduced in Section 2.2.2, refers to the definition and deployment of airport infrastructure by means of well-defined and standardised building blocks, facilities or units which can be installed or removed in a repetitive manner (Kincaid et al., 2012). For this study, a module used for check-in facilities is considered to consist of a predefined number of check-in desks as well as the necessary building space for check-in desks as well as for queueing and circulation of passengers.

(iii) *Evaluation 3* is an extension of *Evaluation 1*. Given the basic flexibilities introduced in *Evaluation 1*, i.e. the *option to defer* and the *option to alter* the scale, the introduction and usage of *buffer space* in *Check-in 1 and 3* is analysed. A buffer space is a building area that is reserved for future use as a facility. Until a buffer

[22] Trigeorgis (1996) also mentions the *option to abandon*, the *option to switch inputs and outputs* and *corporate growth options*. Engineering systems often have a very low salvage value, which can make the application of the *option to abandon* difficult or even impossible. The *option to switch inputs and outputs* is not applicable to *Check-in 1 and 3* since the check-in process has no inputs and outputs other than passengers. Finally, the *corporate growth option* is usually reserved for projects and systems in the high-tech industry sector as well as for companies which have a strong focus on research and development (Trigeorgis, 1996).

space is converted into a complete facility airport passenger terminal facility, the space either remains unused or is put to interim use, such as for the provision of retail, food and beverage services. To make use of buffer spaces, airport planners must either initially plan, design and build passenger terminals with buffer spaces in mind, or they must designate and reserve existing building areas as buffer spaces. For check-in facilities in particular, buffer space must be planned in such a way that the check-in facility that will be created can be connected to the BHS. For this reason, installation costs for buffer space come with a cost premium which covers all expenses resulting from the required integration with the BHS.

Table 5.1 summarises all real options investigated for *Check-in 1 and 3* in this study.

Real option	*Evaluation 1*	*Evaluation 2*	*Evaluation 3*
Options to defer & alter	✓	✓	✓
Modular development		✓	
Buffer space			✓

Table 5.1: Candidate flexibilities evaluated in the proposed planning example on *Check-in 1 and 3* at ZRH Airport.

5.1.4 Value of flexibility

For the candidate flexibilities introduced above, both conventional and flexible facility requirements for *Check-in 1 and 3* at ZRH Airport are determined. Conventional facility requirements are created with the baseline model and fixed model, while flexible facility requirements are generated with the CGDRM and RFDRM. Facility requirements that have been created with different CEP models can be compared with each other by means of their *value of flexibility (VoF)* (Cardin, 2014; Cardin & Hu, 2016; Cardin et al., 2015; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018), which is defined as follows:

$$VoF_{\text{Flexible System}} = \max\left(ENPV_{\text{Flexible System}} - ENPV_{\text{Benchmark}}, 0\right) \tag{5.1}$$

where $ENPV_{\text{Flexible System}}$ and $ENPV_{\text{Benchmark}}$ describe the ENPV of a flexible engineering system and a conventional system acting as a benchmark, respectively. For the purpose of this planning example, the VoF of facility requirements generated with the fixed model, the CGDRM or the RFDRM is defined as follows

$$\begin{aligned} VoF_{\text{Fixed Model}} &= ENPV_{\text{Fixed Model}} - ENPV_{\text{Baseline}} \\ VoF_{\text{CGDRM}} &= ENPV_{\text{CGDRM}} - ENPV_{\text{Baseline}} \\ VoF_{\text{RFDRM}} &= ENPV_{\text{RFDRM}} - ENPV_{\text{Baseline}}. \end{aligned} \tag{5.2}$$

In contrast to the literature, the definition of VoF applied in this study also allows for negative values. This extension of Equation 5.1 permits an objective evaluation of facility requirements that perform worse than the benchmark. Furthermore, the VoF is also calculated for conventional facility requirements which are created with the fixed model. From a purely technical point of view, the term *value of flexibility* is incorrect in this case, as conventional facility requirements are not flexible by definition. However, since the calculation procedure specified in Equation 5.2 is identical for all CEP models and the term VoF is well established in the literature, it was decided to keep the term VoF, even when applied to conventional facility requirements.

5.2 Inventory and parametrisation

This section comprises of the inventory of *Check-in 1 and 3* at ZRH Airport as well as references to the parametrisation applied to the demand and CEP models used in the context of this planning example. Unless otherwise mentioned, information which the inventory and the parametrisation presented in this section is based on was provided by the planning department of Flughafen Zürich AG (FZAG).

Inventory. In 2019, a total of 45 check-in desks[23] were available in *Check-in 1*, while there were 33 desks in *Check-in 3* (FZAG, 2020). Of the 78 check-in desks in *Check-in 1 and 3*, 69 desks were dedicated to *Swiss International Airlines* and its *Star Alliance* partner airlines. Based on the actual infrastructure usage in 2019, it was found that of the 78 check-in desks, 53 desks were used by *Swiss International Airlines* and its partner airlines during the design hour of the year 2019. Check-in desks installed at ZRH Airport require on average a building space area of $A_{K,CH} = 7\,\mathrm{m}^2$. Further, based on operational experience of FZAG, the average process time per passenger at a *Check-in 1 and 3* is known to be $PT_{CH} = 60\,\mathrm{s}/\,\mathrm{PAX}$, which corresponds to an average service rate of $\mu_{K,CH} = 60\,\mathrm{PAX}/\,\mathrm{h}$ for each check-in desk.

As summarised in Table 5.2, the total building area occupied by *Check-in 1 and 3* is $4051\,\mathrm{m}^2$ and can be allocated to the following uses: $506\,\mathrm{m}^2$ is taken up by the check-in desks themselves, $1423\,\mathrm{m}^2$ is area allocated for passengers in queues and $2122\,\mathrm{m}^2$ is circulation area for passengers and staff. At present, no building areas are designated as buffer space.

Concerning service quality, FZAG applies the LoS concept presented in IATA (2017), see Section 2.1.3. FZAG considers a check-in facility to be optimally designed if the average maximum queueing time (MQT) experienced by passengers during the design hour is between $MQT_{CH}^{min} = 5\,\mathrm{min}/\,\mathrm{PAX}$ and $MQT_{CH}^{max} = 10\,\mathrm{min}/\,\mathrm{PAX}$. FZAG also aims to provide each passenger with an individual queueing space of $A_{Q,CH} = 2\,\mathrm{m}^2/\,\mathrm{PAX}$ on average.

Table 5.3 summarises the observed demand in the years 2009 to 2019 at ZRH Airport in general, and for *Check-in 1 and 3* in particular. Columns $\frac{\mathrm{ATM}}{\mathrm{yr}}$, D_t and $D_{CH,t}$, refer to the observed total annual aggregated demand in ATMs, total annual aggregated pas-

[23] Besides conventional check-in desks, a total of 26 self-service check-in machines were available in *Check-in 1 and 3* in 2019. According to the planning specifications of FZAG, no facility requirements for self-service machines are determined in this study. Based on statements from planning experts at FZAG, self-service check-in equipment can be easily integrated into existing check-in facilities due to the small footprint of the devices.

Item	Unit	Available in 2019	Used in 2019
Circulation area	m^2	2122	2122
Waiting area	m^2	1423	1423
Desk area	m^2	506	506
Total Building Area	m^2	4051	4051
Check-in desks	desks	69	53

Table 5.2: Inventory of *Check-in 1 and 3* facilities used by *Swiss International Airlines* and partner airlines at ZRH Airport.

sengers and total annual aggregated local-outbound[24] passengers using *Check-in 1 and 3*, respectively. Column $PAXATM^{dh}_{CH,t}$ refers to the average number of passengers per ATM during the design hour of year t who have used *Check-in 1 and 3*. Finally, column $d_{CH,t}$ refers to the observed DHL demand of *Check-in 1 and 3*.

The aggregated demand data as well as $PAXATM^{dh}_{CH,t}$ have been provided by FZAG. DHL demand for *Check-in 1 and 3* was determined by the author by applying the following procedure. In a first step, PTS data describing passenger influx to the boarding pass control facility at ZRH Airport for the years 2009 to 2019 was analysed using the *rolling maximum algorithm* presented in Section 4.2.2. Since the boarding pass control facility is located after *Check-in 1 and 3*, it is assumed that the temporal distribution of demand at both facilities is very similar. However, in terms of volume, demand at check-in is expected to be less pronounced than at the boarding pass control facility, since not all local-outbound passengers have to use the check-in facility. Indeed, some passengers travel without luggage and can therefore proceed directly to the security checkpoint facility upon arrival at the airport. For this reason, FZAG assumes that only $p_{CH} = 80\,\%$ of all passengers passing through the boarding pass control facility also use check-in. In a second step, DHL demand for *Check-in 1 and 3* was determined according to Waltert et al. (2021):

> … by means of the SBR referring to the 20$^{\text{th}}$ highest hour of passenger flow of the entire year. This contrasts with the literature, which recommends

[24] *Local-outbound passengers* includes all travellers who start their journey at an airport. Transit passengers are not counted as local-outbound passengers.

using the 30th highest hour for the SBR (Ashford et al., 2013; Matthews, 1995). According to ZRH Airport, the rationale behind opting for the SBR based on the 20th hour is grounded on considerations regarding the public's perception of service quality. Due to the operational concept of the local hub airline, most passenger terminal facilities at ZRH Airport experience only one daily peak period, whose duration is usually rather short. Consequently, by selecting a very restricting 20th highest hour for the DHL, the number of days on which customers might experience unacceptable service levels during this daily peak period can be limited significantly. (p. 4)

Year	$\frac{\text{ATM}}{\text{yr}}$	D_t	$D_{CH,t}$	$PAXATM^{dh}_{CH,t}$	$d_{CH,t}$
Unit	*ATM*	*MPPA*	*MPPA*	*PAX per ATM*	*PAX/h*
2009	223 333	21.91	3.458	79	3239
2010	227 815	22.85	3.699	92	3302
2011	238 569	24.31	4.026	115	3785
2012	233 064	24.79	4.095	106	3958
2013	228 314	24.85	4.327	100	3810
2014	230 652	25.45	4.484	110	4396
2015	231 095	26.25	4.785	85	4059
2016	235 931	27.61	5.045	104	4212
2017	236 418	28.27	5.296	88	4507
2018	244 430	31.08	5.891	92	4452
2019	243 115	31.48	6.066	109	4892

Table 5.3: Observed annual aggregated passengers and air traffic movements at ZRH Airport and DHL demand of *Check-in 1 and 3* for the years 2009 to 2019.

Parametrisation. The demand models and CEP models used in this study need to be parametrised. For this purpose, parameters provided by FZAG are used. The reader is referred to Appendix A for an overview an all parameters applied.

5.3 Generation of demand scenarios

Demand scenarios are generated in a process consisting of two steps: First, annual aggregated passenger demand scenarios for ZRH Airport are created by means of the annual aggregated demand model presented in Section 4.1. Next, the annual aggregated demand scenarios are converted into DHL demand scenarios for *Check-in 1 and 3* with the unsaturated DHL model and the saturated DHL model introduced in Sections 4.2.3 and 4.2.4, respectively.

5.3.1 Annual demand model

For ASP projects, planning horizons of typically 20 to 50 years are selected, see Section 2.1. This planning example considers a planning horizon of $T = 20$ years, which is further divided into 20 equally spaced planning phases $t = 1, 2, \ldots, 20$. Annual aggregated demand scenarios $\boldsymbol{\xi}^s$ are created for ZRH Airport using the annual aggregated demand model introduced in Section 4.1. Each scenario $\boldsymbol{\xi}^s = \left[\xi_1^s, \xi_2^s, \ldots, \xi_T^s\right]$ is a vector consisting of 20 elements ξ_t^s which each describe annual aggregated demand in year t. For this planning example, the future aggregated annual demand scenarios for ZRH Airport are based on the observed demand in the year 2019. Thus, demand of the years 2020 and 2021, which turned out to be exceptionally low due to the economic downturn following COVID-19, is not taken into account for the generation of future demand scenarios. Demand for air transportation is expected to return to 2019 levels in the coming years (Eurocontrol, 2021). However, it is currently uncertain when future demand will again surpass the 2019 level. For this reason, the time axes of all plots presented in this study are labelled with planning phases t only and do not refer to specific years. In this way, the results presented in this study can be used at a later date when demand recovers.

The annual aggregated demand model is based on a GBM model, which requires appropriate parametrisation for the initial annual aggregated demand D_0, the average percentage drift rate μ_D and the percentage volatility σ_D. D_0 is assumed to be equal to the observed annual demand in year 2019, which is $\hat{D}_0 = 31\,478\,748\,\text{PAX}$. Further, according to De Weck et al. (2007), μ_D and σ_D can be estimated with the sample mean and the sample standard deviation of the observed relative demand growth $\frac{D_{t+1}}{D_t}$, respectively. Given the observed annual passenger demand data for years 2009 to 2019 presented in column D_t of Table 5.3, percentage drift and volatility of demand growth at ZRH Airport are estimated as $\hat{\mu}_D = 3.723\,\%$ and $\hat{\sigma}_D = 2.699\,\%$. The standard error of the estimated drift rate is quantified by means of Equation 4.2 as $\hat{\sigma}_{\mu_D} = 0.814\,\%$, while the standard error of the estimated volatility is approximated with Equation 4.3 as $\hat{\sigma}_{\sigma_D} \approx 0.604\,\%$.

Finally, a set $\Omega = \{\boldsymbol{\xi}^1, \boldsymbol{\xi}^2, \ldots, \boldsymbol{\xi}^S\}$ consisting of $S = 5000$ independent realisations[25] of annual aggregated passenger demand scenarios $\boldsymbol{\xi}^s$ is generated with the annual aggregated demand model. In Figure 5.2, 100 randomly selected annual passenger demand vectors $\boldsymbol{\xi}^s \in \Omega$ generated by this process are depicted for illustrative purposes.

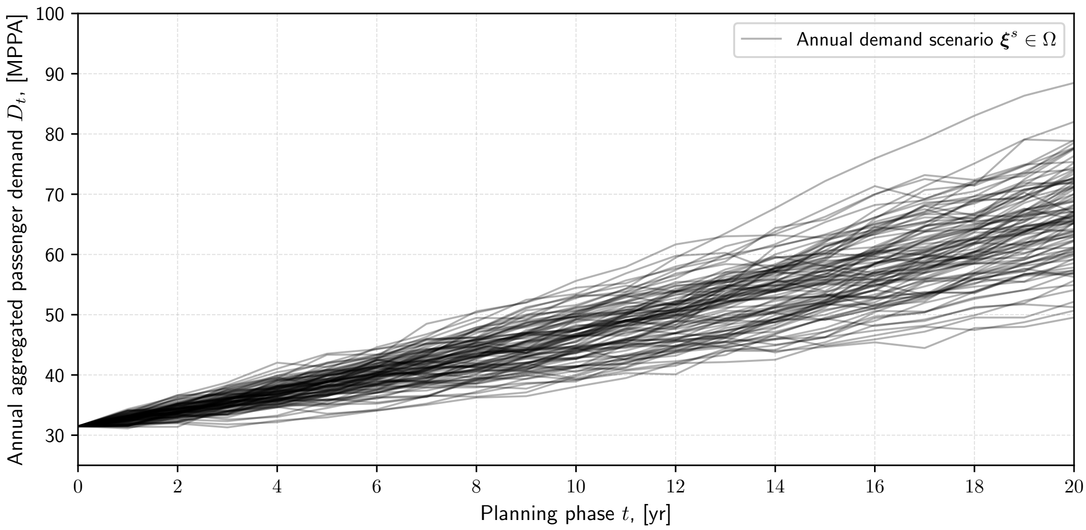

Figure 5.2: Annual aggregated passenger demand scenarios for ZRH Airport. The figure depicts 100 randomly selected realisations of $\boldsymbol{\xi}^s \in \Omega$.

[25] As mentioned in Section 2.3.3.2, the literature recommends the generation of 2000 to 10000 independent demand scenarios.

5.3.2 DHL model

The annual aggregated passenger demand scenarios $\xi^s \in \Omega$ are converted into DHL demand scenarios $\mathbf{d}^s_{CH}$ by means of the unsaturated and saturated DHL models introduced in Section 4.2.

5.3.2.1 Unsaturated model for Check-in 1 and 3 at ZRH Airport

The unknown coefficients $\beta^{US}_{CH,0}$ and $\beta^{US}_{CH,1}$ of the unsaturated DHL model, see Equation 4.4 on page 98, are estimated with the ordinary least squares method, given a total of 11 observations of annual aggregated demand D_t at ZRH Airport and DHL demand $d_{CH,t}$ of the check-in facilities as indicated in Table 5.3. A coefficient of determination of R^2 =0.845 and a root mean squared error of $RSME$ =279 are achieved by the linear regression model underlying the unsaturated DHL model. Thus, the unknown coefficients of the model are estimated as $\hat{\beta}^{US}_{CH,0} = -8.76 \times 10^4$ $(p < 0.05)$ and $\hat{\beta}^{US}_{CH,1} = 5.34 \times 10^3$ $(p < 0.05)$.

In Figure 5.3, the observed annual aggregated passenger demand data for ZRH Airport is illustrated "with blue ... dots, while the best fit of the unsaturated DHL model, [which is] based on the transformation function mentioned in [Equation 4.4 on page 98], is displayed as a red line ... . [T]he corresponding 95 % confidence interval [of the unsaturated DHL model] is illustrated with black dashed lines" (Waltert et al., 2021, p. 6). Further, the observed DHL versus the predicted DHL plot in Figure 5.3 depicts residuals of the unsaturated DHL model.The predicted DHL expresses the response of the unsaturated DHL model, given the observed DHL demand from years 2009 to 2019 as the inputs of the model.

5.3.2.2 Saturated model for Check-in 1 and 3 at ZRH Airport

For the saturated DHL model, see Section 4.2.4, the following inputs are required: (i) the parametrisation of the passenger per air traffic movement (PAXATM) model, (ii) ratio $\hat{r}_{CH}$ and (iii) the maximum departure throughput capacity $\hat{\mu}_R$ of the runway system of ZRH

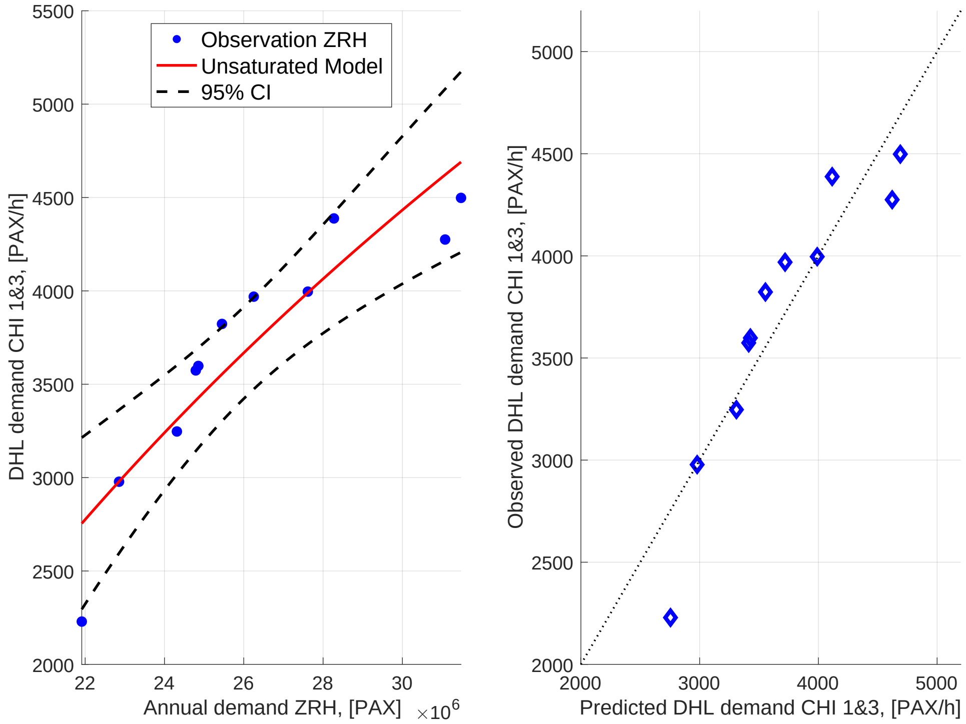

Figure 5.3: Unsaturated DHL model for *Check-in 1 and 3* at ZRH Airport fitted to observed DHL data for years 2009 to 2019. Adapted from Waltert et al. (2021, p. 7).

Airport.

The unknown coefficients $\beta_0^{PA}, \beta_1^{PA}, \beta_2^{PA}$ and β_3^{PA} of the PAXATM model, see Equation 4.5 on page 101, are estimated with the ordinary least squares method by fitting the model to the dataset depicted in Figure 4.5 on page 101. The runway system at ZRH Airport consists of 3 runways, on which, however, aircraft movements cannot take place at the same time for operational and political reasons. For this reason, the PAXATM model is fitted to a subset of the above-named dataset, namely to data of airports with only 2 and 3 runways.

The PAXATM model fits the data (764 observations) with a coefficient of determination of $R^2 = 0.751$ and a *RSME* of 18.6. Subsequently, the estimated parameters of the PAXATM model are $\hat{\beta}_0^{PA} = -2.52 \times 10^3$ $(p < 0.05)$, $\hat{\beta}_1^{PA} = 4.18 \times 10^2$ $(p < 0.05)$, $\hat{\beta}_2^{PA} = 9.72 \times 10^{-1}$ $(p < 0.05)$ and $\hat{\beta}_3^{PA} = -1.57 \times 10^2$ $(p < 0.05)$. The left diagram in

Figure 5.4 depicts how well the parametrised PAXATM model fits the "input data of airports with 2 to 3 runways (blue dots). The data of ZRH Airport ... is highlighted in magenta ... . The best model fit, in this case for an airport with 2 runways, is displayed as a red line, while the 95 % confidence interval is shown with black dashed lines" (Waltert et al., 2021, p. 6). Further, similar to Figure 5.3, the right diagram in Figure 5.4 illustrates the residuals of the PAXATM model.

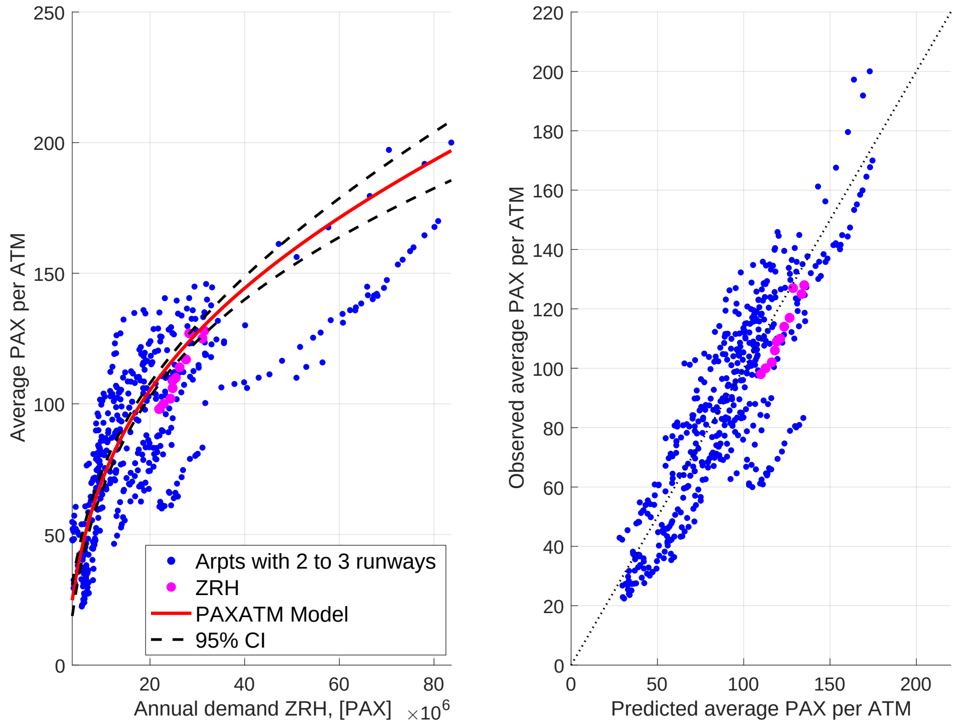

Figure 5.4: Fitted PAXATM Model to 764 PAXATM observations of airports with 2 and 3 runways and for year 2019. From Waltert et al. (2021, p. 7).

To estimate ratio r_{CH} which expresses the relationship between $PAXATM^{dh}_{CH,t}$ and $PAXATM_t$, observational data of ZRH Airport and *Airport 2* presented in Figure 4.6 on page 103 is used. From the data presented in Figure 4.6, it can be inferred that ratio r_{CH} is somewhat volatile, since it covers a range between 0.7 to 1.3 Thus, it was decided to approximate the value of the ratio for *Check-in 1 and 3* at ZRH Airport at $\hat{r}_{CH} = 1.00$. Finally, according to Waltert et al. (2021, p. 5), "the maximum departure throughput capacity of the runway system [$\hat{\mu}_R$ of ZRH Airport] is known to be 44 ... [aircraft] movements per hour."

5.3.2.3 Conversion of annual demand scenarios to DHL demand scenarios

Given both the unsaturated DHL model and the saturated DHL model parametrised for *Check-in 1 and 3* at ZRH Airport, the annual aggregated passenger demand scenarios $\boldsymbol{\xi}^s \in \Omega$ presented in Section 5.3.1 are converted into corresponding DHL scenarios $\mathbf{d}^s_{CH}$ for *Check-in 1 and 3*, where the procedure described in Section 4.2.5 is applied. In Figure 5.5, 100 randomly selected DHL demand scenarios for *Check-in 1 and 3* are depicted for illustrative purposes. For every DHL demand scenario $\mathbf{d}^s_{CH}$, the part of the scenario determined with the unsaturated DHL model is plotted in red, while the saturated DHL demand part is drawn in black.

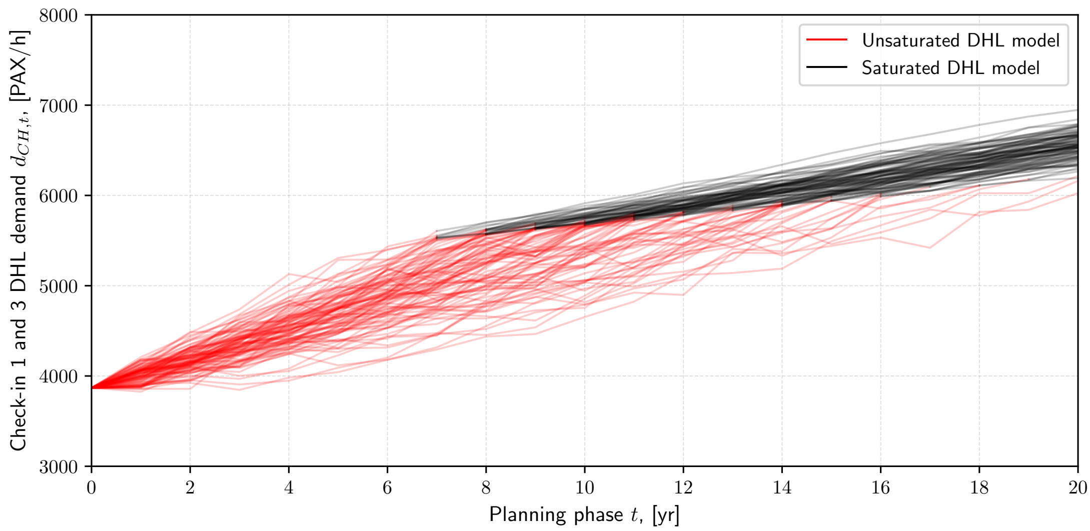

Figure 5.5: DHL demand scenarios for *Check-in 1 and 3* at ZRH Airport. Red lines refer to results of the unsaturated DHL model, while black lines refer to results of the saturated DHL model. Figure shows 100 randomly selected DHL demand scenarios.

5.4 Evaluation of candidate flexibilities

In this section, optimal facility requirements for three different candidate flexibilities for *Check-in 1 and 3* defined in Section 5.1.3 are presented. In a first step, the input variables and parameters which have a particularly strong influence on the results of the CEP models used to determine facility requirements are identified in Section 5.4.1. Secondly, *Evaluation 1, 2 and 3* are carried out successively in Sections 5.4.2, 5.4.3 and 5.4.4. For this purpose, optimal conventional and flexible facility requirements for *Check-in 1 and 3* are determined by means of the fixed model, the CGDRM and the RFDRM. These facility requirements are compared with the outputs of the baseline model in order to determine their resulting VoF. Also, the conventional and flexible facility requirements are examined for their sensitivity to changes in the input variables and parameters that have been identified as particularly influential.

5.4.1 Sensitivity analysis of CEP models

The results of a CEP model depend significantly on the parameters used. In this section, the parameters that have a large influence on the models' results are determined by means of a sensitivity analysis. Starting from the default parametrisation defined in Appendix A, the effect of a change of the value of a single parameter on the result of the CEP models is quantified *ceteris paribus*[26]. In order to estimate the influence of the parametrisation on the CEP model's results, the fixed model, the CGDRM and the RFDRM are used to create optimal facility requirements for *Check-in 1 and 3* and *Evaluation 1*[27]. In a first step, the resulting ENPV of the facility requirements determined with all the CEP models, given default parametrisation, hereafter denoted as $ENPV_{\text{Default}}$, are calculated. In a second step, the parameters of the demand and NPV valuation models are modified on an individual basis, i.e. *ceteris paribus*, by $\pm 10\,\%$ from their default value. For each parameter

[26] *Ceteris paribus* is Latin for "every thing else being equal".

[27] The sensitivity analysis has been conducted for $S = 5000$ independent realisations of aggregated annual passenger demand scenarios $\boldsymbol{\xi}^s \in \Omega$.

variation, the ENPVs of the resulting optimal facility requirements, which are referred to as $ENPV_{\text{Variation}}$ in the following, are determined. Finally, the influence of a parameter variation on the results of the CEP models is quantified as $ENPV_{\text{Variation}} - ENPV_{\text{Default}}$. The larger this difference becomes, the stronger is the influence of the parameter on the results of the CEP models.

In the literature, e.g. De Neufville and Scholtes (2011) or Mun (2002), the results of a sensitivity analysis are often illustrated with a *tornado diagram*. A tornado diagram is a horizontal bar diagram that shows how the parameters influence the outputs of a model. For this purpose, the relative change of the model's result, i.e. the change in the ENPV of *Check-in 1 and 3* caused by the change in a parameter's value, is considered. The bars of the tornado diagram are ordered in such a way that the parameter which has the greatest influence on a model's outputs is displayed at the top of the tornado diagram, while the least important parameter is shown at the bottom. In this way, a funnel-like diagram structure results, which originally gave the diagram its name. Also, to show in which way a parameter affects the results, solid bars indicate how the CEP model is affected by a $+10\,\%$ change of the parameter, while white bars depict the model's response given a change of $-10\,\%$.

In Figure 5.6, the results of the sensitivity analysis conducted for the fixed model are summarised. From data presented in Figure 5.6, it can be inferred that revenue function parameters $r_{PAX,CH}$ and $r_{K,CH}$ affect the output of the fixed model most. The model's response to positive and negative changes of the revenue function parameters is almost symmetrical, which, according to De Neufville and Scholtes (2011), is an indication that the parameters are not subject to the *flaw of averages*. For most of the remaining parameters, however, asymmetries can be observed. This is an indication that some parameters are subject to the *flaw of averages*, as discussed in Section 2.4.3. Considering the magnitude of the influence, it can be stated that, besides the above-mentioned parameters of the revenue function, the discount rate δ and the EoS parameter α_K have the greatest effect on the fixed model. Figure 5.6 also suggests that variations in the parameters of the annual

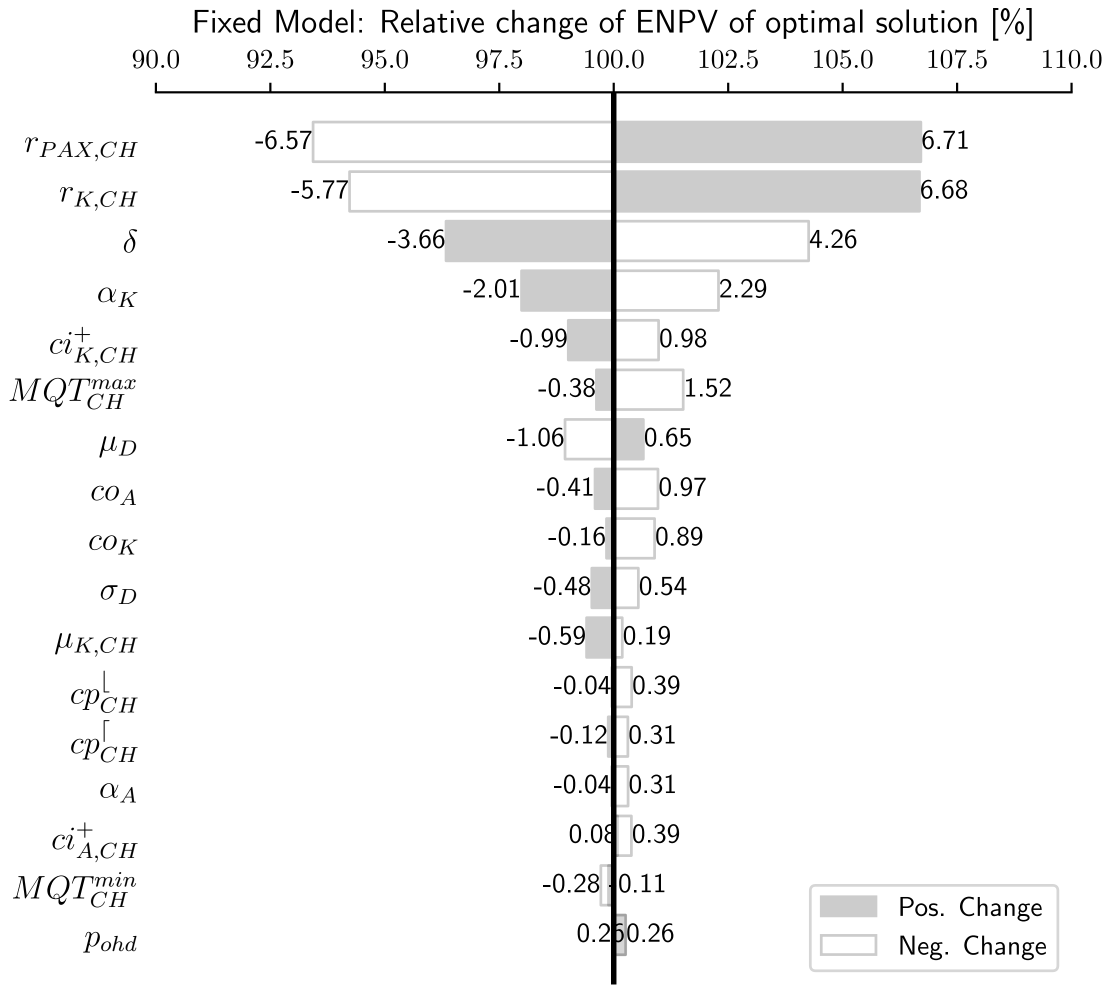

Figure 5.6: Tornado diagram depicting the results of a sensitivity analysis carried out for the fixed model for *Check-in 1 and 3* and *Evaluation 1*.

aggregated demand model, μ_D and σ_D, affect the output of the fixed CEP model only marginally. While σ_D appears to affect the results nearly symmetrically, negative changes in μ_D seem to influence the model's result more than positive ones. Further, the fixed model is more resistant to changes in parameters specifying the penalty cost function, i.e. MQT^{max}_{CH}, $cp^{\lceil}_{CH}$, $cp^{\lfloor}_{CH}$ and $\mu_{K,CH}$.

The identical sensitivity analyses have also been carried out for the CGDRM and the RFDRM. Detailed results of these are shown in Figures B.1 and B.2 in Appendix B. The tornado diagrams of the fixed model, the CGDRM and the RFDRM presented show very similar results, both in the order of the significant parameters and in the magnitude of the numbers presented. For this reason, it is assumed that the data shown in Figure 5.6 is representative for all CEP models used in this planning example.

Based on the data shown in Figure 5.6, it was decided to examine the influence of the discount rate δ, the EoS parameter α_K and α_A, the annual aggregated demand parameters μ_D and σ_D, and also the average service rate $\mu_{K,CH}$ in more detail in *Evaluations 1, 2 and 3*. Parameters δ, α_K and α_A have been selected for further investigation given their strong influence on the CEP models' results. The influence of variations in the annual aggregated demand parameters μ_D and σ_D as well as the average service rate $\mu_{K,CH}$ are examined in more detail, since, as stated in Section 5.1.2, demand and the service rate of check-in desks are subject to uncertainty. Finally, despite their strong influence on the model results, revenue function parameters $r_{PAX,CH}$ and $r_{K,CH}$ are not considered further in this study, since they are controlled exclusively by FZAG, i.e. through the *airport charges regulation* document (FZAG, 2021), etc.

5.4.2 Evaluation 1 – Options to defer and alter the scale

Evaluation 1 considers the *option to defer* and the *option to alter the scale* of the future development of *Check-in 1 and 3* at ZRH Airport. Based on $S = 5000$ independent realisations of annual aggregated passenger demand scenarios for a planning horizon of $T = 20$ years and the default parametrisation presented in Section 5.2 and Appendix A, conventional as well as flexible facility requirements are determined with the fixed model, the CGDRM and the RFDRM.

5.4.2.1 Optimal facility requirements

The optimal solution candidates generated with the CEP models for *Evaluation 1* as well as the resulting ENPVs of *Check-in 1 and 3* are summarised in Table 5.4. Optimal facility requirements determined with the baseline model and the fixed model are expressed in terms of capacity vectors. The baseline model proposes that airport planners add $\Delta K^*_{CH,0} = 28$ check-in desks to *Check-in 1 and 3* at $t = 0$, while the fixed model determines an optimal capacity vector $\mathbf{K}^*_{CH}$, which specifies the required number of check-in desks for all planning phases t. In contrast, the CGDRM and the RFDRM specify optimal flexible facility requirements by means of decision rules. For the CGDRM, the optimal parametrisation of conditional-go decision rule $\mathcal{D}_{\boldsymbol{\theta}}$ is $\theta^*_1 = 7$ desks and $\theta^*_2 = -1$ desk. Consequently, expressed in terms of the logical *IF-THEN-ELSE* operator, airport planners would be advised to add 7 check-in desks to the system as soon as the difference between the throughput $\tau^s_{CH,t}$ of the check-in facility and the observed DHL demand $d^s_{CH,t}$ in planning phase t is less than -1 desk multiplied by the unit service rate $\mu_{K,CH}$. Given the comparatively small solution space of the CGDRM, the near-optimal results determined with the proposed GA-based solution procedure was compared with the ground truth, which was obtained by means of enumeration. It was thus confirmed that the quality of the near-optimal solution generated with the GA was very good, as it is identical to the ground truth. For the RFDRM, the optimal decision rule $\mathcal{L}^*$ used to calculate the priority index $\lambda^s_{l,t}$ of adjustment options[28] $e_l \in e$ is defined as a function of both the difference between capacity $K^s_{CH,t-1}$ and DHL demand $d^s_{CH,t}$, as well as the installation costs of option e_l.

Figure 5.7 shows the above-mentioned optimal facility requirements for *Check-in 1 and 3* in graphical form as a *capacity deployment plot*. This is a figure that specifies how capacity is adjusted best over time. Conventional facility requirements are defined as capacity vectors which are identical for all demand scenarios. For this reason, the optimal capacity deployment sequence for the baseline model and the fixed model is indicated by a grey and a red solid line, respectively. Flexible facility requirements, however, are defined as optimal decision rules that result in an independent capacity deployment sequence for each demand scenario. For the sake of readability, not all the capacity deployment sequences for flexible facility requirements are plotted, but rather the probability that a certain capacity level is operational at a certain planning phase t is indicated by means of bubbles. The larger the area of these bubbles, the greater the probability that the

[28]For *Evaluation 1*, the set of adjustment options e was defined as follows: $e = \{0, 1, 2, \ldots, 50\}$. See Appendix A for a complete overview and description of all parameters applied in *Evaluation 1*.

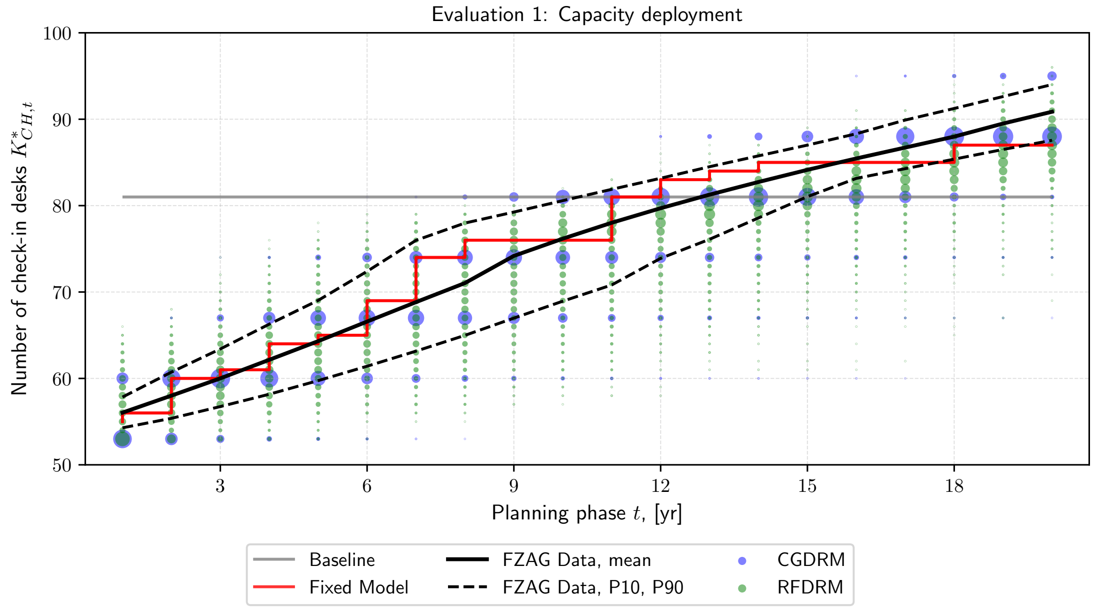

Figure 5.7: Optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 1*.

operational capacity of *Check-in 1 and 3* will have this value at a respective point in time. Blue bubbles in Figure 5.7 refer to the capacity deployment of the CGDRM, while green bubbles refer to the RFDRM. The capacity deployment sequences based on the optimal conventional and flexible facility requirements for *Check-in 1 and 3* can be compared with planning data provided by FZAG. Currently, FZAG uses a simple capacity planning model which is based on a linear regression model. This model[29] allows the determination of a capacity deployment sequence for *Check-in 1 and 3* based on a DHL demand scenario. The solid black line in Figure 5.7 indicates the capacity deployment sequence according to FZAG's model for an average demand scenario, while the black dashed lines represent the capacity deployment sequences for the 10 % and 90 % percentile demand scenarios.

Table 5.4 further shows that for *Evaluation 1* flexible facility requirements for *Check-in 1 and 3* lead to a higher ENPV of the system than conventional facility requirements.

[29]The capacity planning model employed by FZAG is not a CEP model. For this reason, this model does not allow the determination of optimal facility requirements, but rather only allows the conversion of a DHL demand into a capacity vector by means of a linear regression model.

As such, facility requirements created with the CGDRM perform best for *Evaluation 1*, resulting in an ENPV of 11 180.70 Swiss Franc (CHF). In relative terms, the ENPV of facility requirements determined with the CGDRM is 0.58 % higher than the ENPV of the RFDRM, and is 4.05 % higher than the fixed model and 5.90 % higher than the baseline model.

Model	Optimal facility requirement	ENPV [CHF]
Baseline	$\Delta K^*_{CH,0} = 28$	10 557.00
Fixed Model	$\mathbf{K}^*_{CH} = [\,55, 56, 60, 61, 64, 65, 69, 74, 76, 76, 76, 81, 83, 84, 85, 85, 85, 85, 87, 87\,]$	10 745.80
CGDRM	$\boldsymbol{\theta}^* = [7, -1]$	**11 180.70**
RFDRM	$\mathcal{L}^* = K^s_{CH,t-1} \cdot \frac{K^s_{CH,t-1} - d^s_{CH,t}}{CI(e_l) - 2 * d^s_{CH,t} \cdot \left(K^s_{CH,t-1} - d^s_{CH,t}\right)}$	11 115.70

Table 5.4: Best solution candidates of the baseline model, the fixed model, the CGDRM and the RFDRM for *Check-in 1 and 3* and *Evaluation 1*.

The fixed model, the CGDRM and the RFDRM are solved by means of evolutionary optimization algorithms, which generate minimally different near-optimal solutions for each implementation of the solver. The results shown above are the near-optimal solution of one single run of the solvers. In order to investigate how much the solutions of the models differ between separate runs of the solvers, the CEP models were executed for *Evaluation 1* in 5 independent runs. It transpired that the baseline model yields to a constant ENPV of 10 557.0 CHF in all 5 simulation runs. The results of the other models show slight variations over the 5 runs: the fixed model leads to a mean ENPV of 10 700.98 CHF with a standard deviation of 167.27 CHF, the CGDRM to a mean ENPV of 11 161.50 CHF with a standard deviation of 18.50 CHF and the RFDRM to a mean ENPV of 11 078.08 CHF with a standard deviation of 73.88 CHF. The numeric results of these 5 independent simulation runs can be found in Table B.1 in Appendix B. Due to (i) the resulting minimal differences in the different runs of the CEP models and (ii) the time consumption necessary with the solvers, see Section 5.5, it was decided not to implement batch runs for *Evaluation 2* and *Evaluation 3*.

5.4.2.2 Simulation results

The solid lines in Figure 5.8 depict so-called *target curves* (De Neufville & Scholtes, 2011) which, by means of cumulative probability distributions, indicate the NPV of *Check-in 1 and 3* over all the analysed scenarios of uncertainty, given the optimal facility requirements determined for *Evaluation 1*. To this end, target curves express the probability that optimal facility requirements lead to a NPV of *Check-in 1 and 3* which is lower than or equal to a certain threshold level. The dashed lines in Figure 5.8 indicate the resulting ENPVs of the optimal facility requirements of *Check-in 1 and 3* determined for *Evaluation 1*.

Flexible engineering systems allow practitioners to both capitalise on potential future opportunities as well as to mitigate or the avert negative risks of future developments. The extent to which facility requirements have this capability is often measured by means of the *value at gain (VaG)*, the *value at risk (VaR)*, as well as the *minimum and maximum NPV* values achieved over all scenarios. In this study, the VaG is defined as the cumulative NPV probability of 90 %, which corresponds to the 90th percentile, while the 10th percentile refers to the VaR[30]. As shown in Figure 5.8 and Table 5.5, the optimal facility requirements determined with the CGDRM outperform all other models in terms of their VaG and VaR for *Evaluation 1*. Interestingly, flexible facility requirements determined with the CGDRM and the RFDRM result in nearly equal VaR values, indicating a similar capacity to avert risks. Columns *min. NPV* and *max. NPV* in Table 5.5 indicate the minimum and maximum NPV achieved by all facility requirements determined for *Evaluation 1*. For both minimum and maximum NPV, flexible facility requirements perform significantly better than conventional facility requirements. Finally, the column VoF summarises the resulting VoF which is calculated as defined in Equation 5.2. It is noticeable that flexible facility requirements lead to significantly higher VoF than conventional

[30]The definition of the VaG and VaR used in this study is in line with a large part of the literature (Cardin et al., 2015; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018). However, it has to be mentioned, that there are some authors, such as Cardin (2014), who define the VaG and the VaR as the 95th and the 5th percentile, respectively

facility requirements which were created with the fixed model.

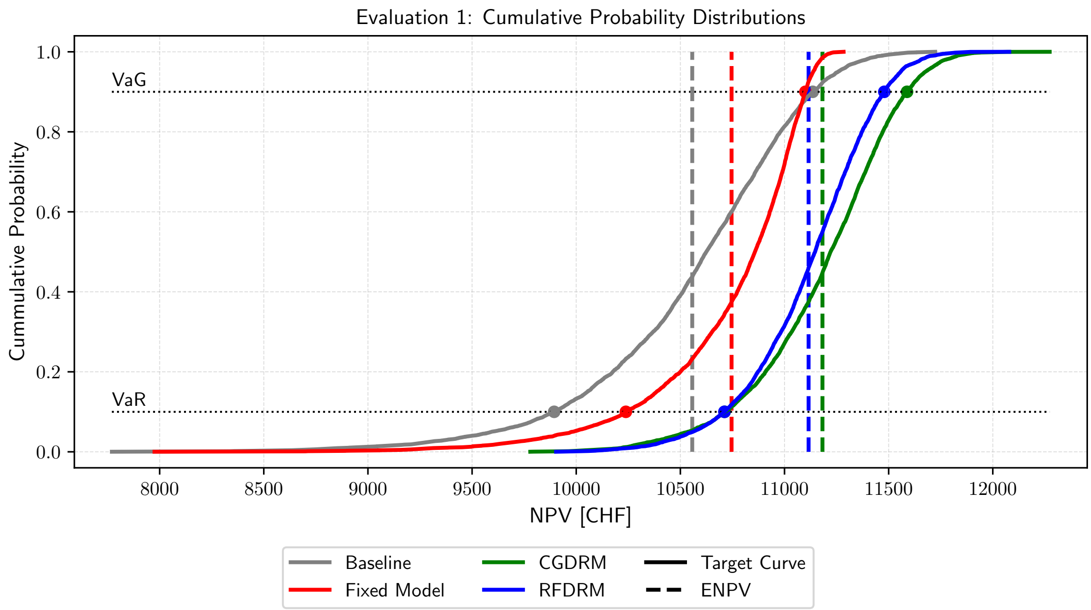

Figure 5.8: Target curves (solid lines) and resulting ENPV (dashed lines) of optimal facility requirements determined with the baseline model (grey), the fixed model (red), the CGDRM (green) and the RFDRM (blue) for *Check-in 1 and 3* and *Evaluation 1*.

Model	ENPV	min. NPV	max. NPV	VaG	VaR	VoF
Baseline	10 557.0	7770.6	11 723.3	11 134.3	9893.8	-
Fixed Model	10 745.8	7975.3	11 283.7	11 099.8	10 238.2	188.8
CGDRM	**11 182.2**	9779.4	**12 273.2**	**11 588.1**	**10 712.4**	**625.2**
RFDRM	11 115.7	**9903.3**	12 079.2	11 478.9	10 711.4	558.7
Best	CGDRM	RFDRM	CGDRM	CGDRM	CGDRM	CGDRM

Table 5.5: Key statistics for *Check-in 1 and 3* and *Evaluation 1*. All figures are given in CHF.

In the literature, a *standard two-sided z-test for mean* is often conducted in order to check whether two target curves created with different CEP models differ significantly from each other (Cardin & Hu, 2016). In this way, the null hypothesis of equal ENPVs resulting from facility requirements generated with different CEP models is tested. For *Evaluation 1*, the ENPV of facility requirements created with the fixed model, the CG-DRM and the RFDRM are compared in a number of z-tests. The results of all z-tests performed are summarised in Table 5.6. Any z-tests with a p-value of less than 1 % are rejected, which means that the simulation results of all the CEP models are significantly different.

	Fixed Model		CGDRM		RFDRM	
	Test-Stat.	*p-value*	*Test-Stat.*	*p-value*	*Test-Stat.*	*p-value*
Baseline	-20.8	$p < 0.01$	-71.0	$p < 0.01$	-65.9	$p < 0.01$
Fixed Model	-	-	-59.6	$p < 0.01$	-53.4	$p < 0.01$
CGDRM	-	-	-	-	$+10.2$	$p < 0.01$

Table 5.6: Two-sided z-test for mean for the results of optimal facility requirements determined with the fixed model, the CGDRM and the RFDRM for *Check-in 1 and 3* and *Evaluation 1*.

5.4.2.3 Sensitivity analysis

To determine how the parametrisation of the CEP models influences optimal facility requirements for *Check-in 1 and 3*, three different sensitivity analyses were conducted: (i) a two-way sensitivity analysis to quantify the impact of the discount rate δ and the EoS parameters α_K and α_A, (ii) a two-way sensitivity analysis to determine how the percentage drift rate μ_D and volatility parameter σ_D affect the results and (iii) a one-way sensitivity analysis to study the impact of the average service rate μ_K. The results of the two-way analyses are depicted in Figures 5.9 and 5.10, while the one-way analysis is shown in Figure 5.11.

Discount rate and EoS parameter. Optimal facility requirements for *Check-in 1 and 3* were created with discount rates in a range of $\delta = 0.02, 0.04, \ldots, 0.20$ and EoS parameter values $\alpha_K = \alpha_A = 0.7, 0.8, 0.9, 1$. For all other parameters, default values as defined in Appendix A were used. The resulting ENPV and VoF of *Check-in 1 and 3* are shown in Figure 5.9. The diagrams in the left column of Figure 5.9 indicate the resulting ENPVs of facility requirements determined with the fixed model (red lines), the CGDRM (green lines) and the RFDRM (blue lines), while the diagrams in the right column depict the resulting VoF. The discount rate δ is plotted on the horizontal axes of the diagrams, while

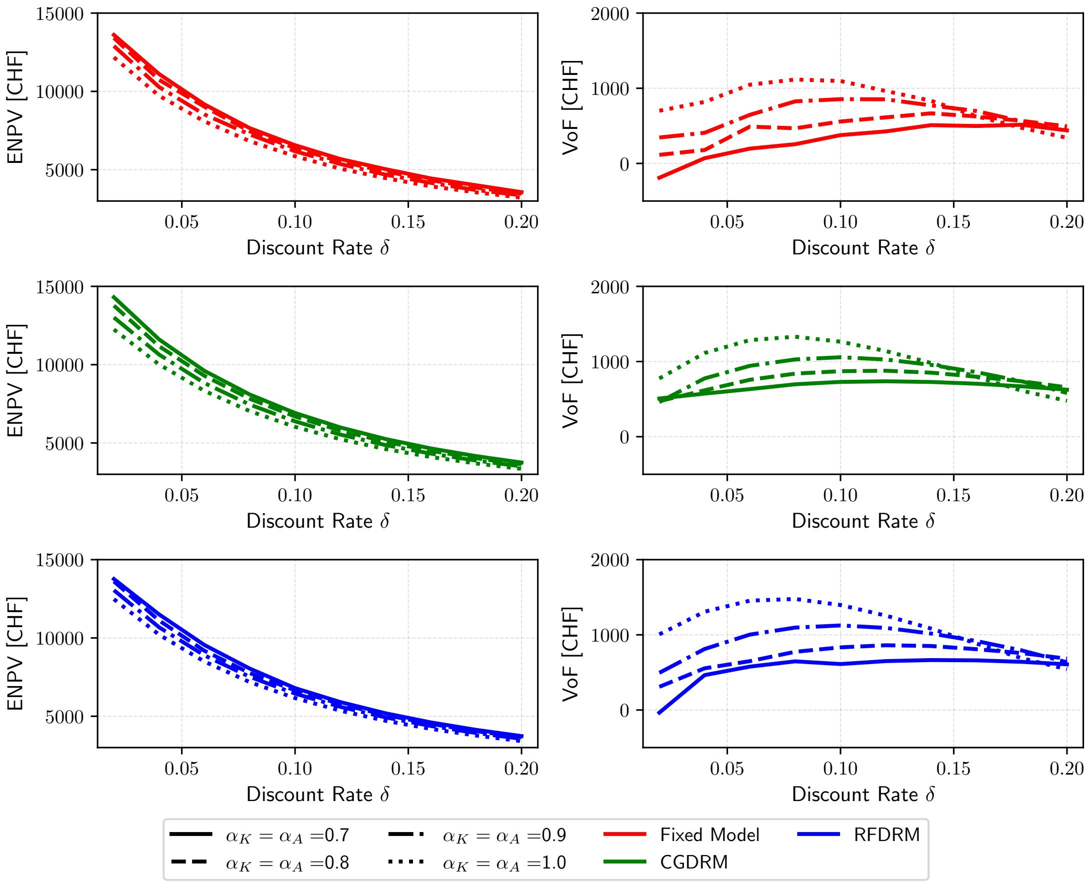

Figure 5.9: Influence of discount rate δ and EoS parameters α_K and α_A on ENPV and VoF of *Check-in 1 and 3* for *Evaluation 1*.

different values for α_K and α_A are indicated by means of various line styles. All in all, the performance of conventional and flexible facility requirements throughout the above-mentioned ranges of the discount rate and EoS parameters are somewhat similar: The ENPV of *Check-in 1 and 3* is negatively affected by both an increase in discount rate δ and an increase in the value of EoS parameters α_K and α_A.

Except for scenarios with discount rates δ larger than approximately 15 %, the VoF of the fixed model, the CGDRM and the RFDRM is positively affected by an increase in EoS parameter values. Where δ is larger than approximately 15 % and the values of α_K and α_A are close to 1, an increase in the EoS parameter values tends to result in a slight decrease of the VoF. Regarding the influence of the discount rate on the VoF, the results show that changes in the discount rate δ tend to lead to more pronounced variations of the VoF if α_K and α_A are close to 1. Additionally, the VoF is positively affected by an increase in the discount rate if δ is smaller than a certain threshold value, while above this threshold value, the opposite applies. The results suggest that this threshold value, which lies in the range of approximately $\delta = 7\,\%$ to $12\,\%$, depends on the CEP model and the EoS parameter value.

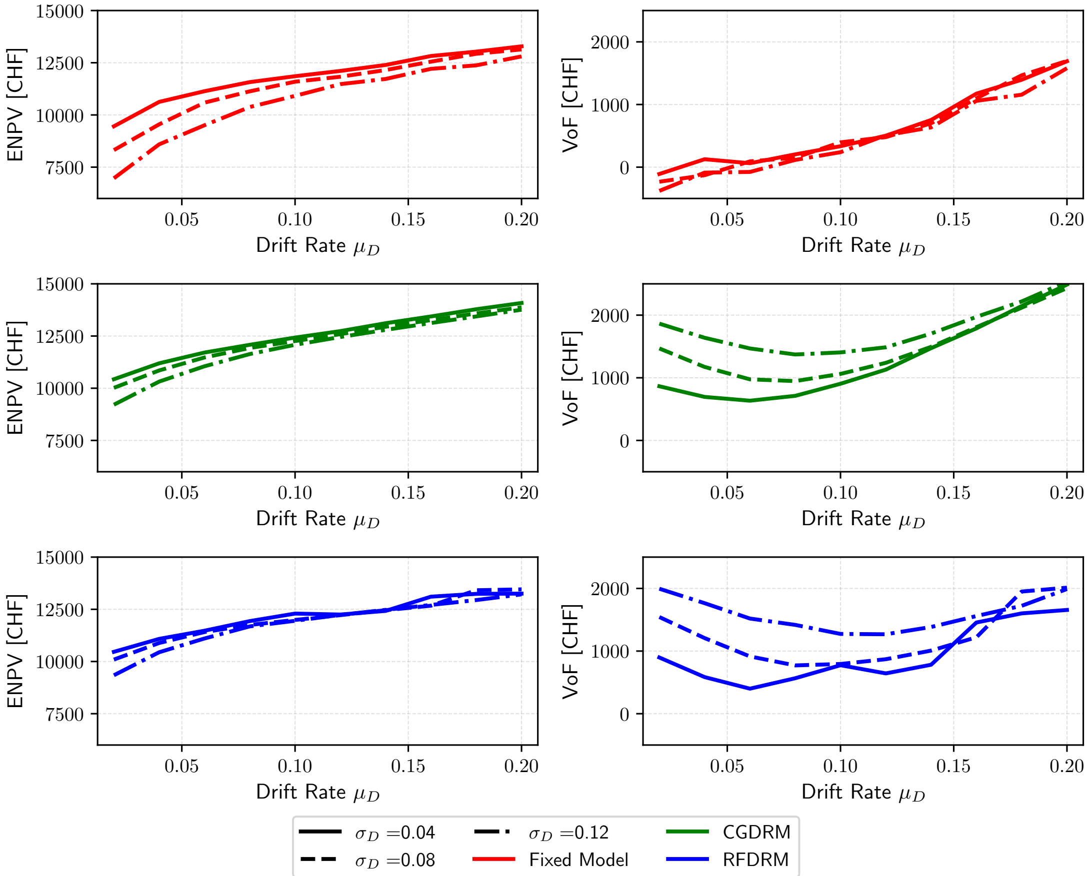

Figure 5.10: Influence of drift rate μ_D and volatility σ_D on ENPV and VoF of *Check-in 1 and 3* for *Evaluation 1*.

Percentage drift rate and demand volatility. In Figure 5.10, the results of the two-way sensitivity analysis for percentage drift rate parameter values $\mu_D = 0.02, 0.04, \ldots, 0.20$ and volatility parameter values $\sigma_D = 0.04, 0.08, 0.12$ are illustrated. The diagrams in the left column of the figure depict the resulting ENPVs of facility requirements determined with the fixed model, the CGDRM and the RFDRM, while the diagrams in the right column show the corresponding VoF. For both conventional as well as flexible facility requirements, the ENPV of *Check-in 1 and 3* appears to be positively affected if μ_D is increased, while the opposite is true for an increase in σ_D. Furthermore, it is also noticeable that flexible facility requirements lead to higher ENPV values than conventional facility requirements.

With regards to the VoF, a clear distinction must be made between the results of the fixed model and those of the flexible CEP models. Throughout the tested range of the percentage drift rate parameter, the fixed model's VoF increases almost linearly as a function of μ_D. Moreover, it appears to be only weakly dependant on the volatility parameter σ_D. On the contrary, the flexible models' VoF seem to depend non-linearly on μ_D. Where values of μ_D are below a certain threshold, VoF decreases with increasing drift rate. Above this threshold, the opposite is true for an increasing percentage drift rate. The results indicate that this threshold rises with increasing volatility; at $\sigma_D = 4\,\%$, the threshold is located at about $\mu_D = 5\,\%$, while at $\sigma_D = 12\,\%$, the threshold is in the region of $\mu_D = 10\,\%$. It should also be noted that for all the tested values of μ_D and σ_D flexible facility requirements lead to higher VoF values than the fixed model. Especially at low percentage drift rates and high demand volatility, flexible facility requirements lead to substantially higher VoF values than for facility requirements determined with the fixed model.

Average service rate. Figure 5.11 illustrates how the ENPV and the VoF of optimal facility requirements for *Check-in 1 and 3* are affected by variations of the average service rate of the check-in desks in a range of $\mu_{K,CH} = 46, 48, \ldots, 86\,\text{PAX/h}$. The results suggest that the ENPV of all CEP models is negatively affected by an increase in the service rate $\mu_{K,CH}$. Particularly noteworthy is the fact that above a service rate of approximately 74 PAX/h, the ENPV of facility requirements created with the fixed model decreases significantly more pronouncedly than it is the case for flexible facility requirements.

Regarding the VoF, the fixed model and the RFDRM show somewhat similar behaviour. Below a certain threshold value of $\mu_{K,CH}$, the VoF increases with increasing $\mu_{K,CH}$, while above this threshold, the VoF decreases. As can be seen in Figure 5.11, this threshold value is located approximately at $\mu_{K,CH} = 74\,\mathrm{PAX/h}$ for the fixed model and $\mu_{K,CH} = 66\,\mathrm{PAX/h}$ for the RFDRM. The VoF of facility requirements determined with the CGDRM, however, is negatively influenced by an increase in the service rate throughout most of the examined range of $\mu_{K,CH}$. Moreover, the CGDRM results in the highest VoF values of all the CEP models.

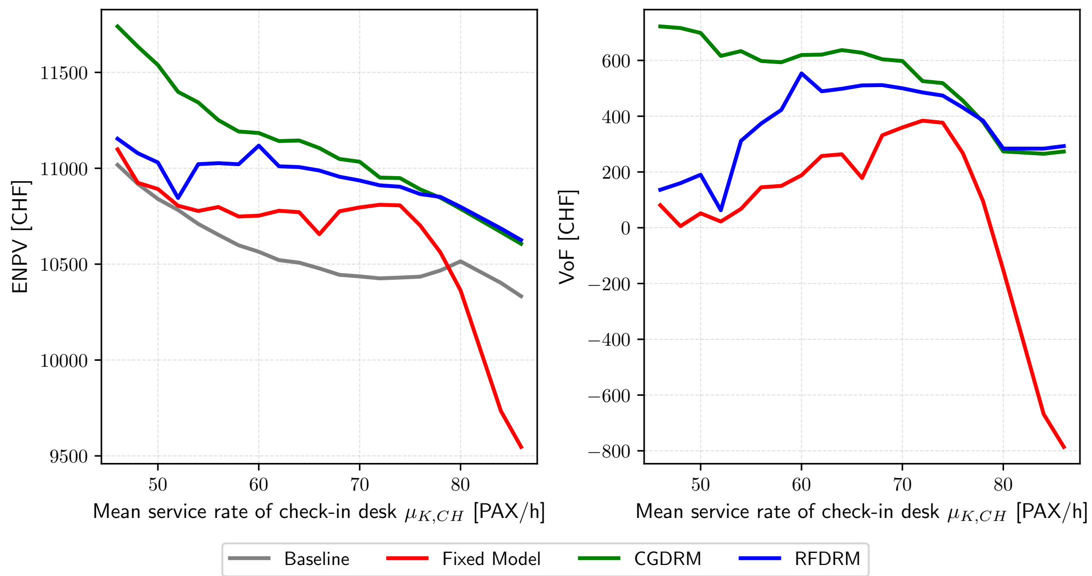

Figure 5.11: Influence of average service rate μ_K on ENPV and VoF of *Check-in 1 and 3* for *Evaluation 1*.

5.4.3 Evaluation 2 – Modular development

Evaluation 2 extends *Evaluation 1* by additionally allowing for *modular development* of *Check-in 1 and 3*. A module is considered a standardised unit consisting of a predefined number of check-in desks, building space for these units as well as building space for queues and circulation of passengers and staff. The size of a module is specified with parameter e_m, which determines the number of check-in desks belonging to one single module. Based on $S = 5000$ independent annual aggregated passenger demand scenarios for a planning horizon of $T = 20\,\mathrm{yr}$ and the default parametrisation presented in Section 5.2 and Appendix A, conventional as well as flexible facility requirements are determined for *Check-in 1 and 3* for module sizes in a range of $e_m = 1, 2, \ldots 35$ check-in desks. In order to allow for modular development, the CEP models presented in this study have to be slightly adapted as follows:

- *Baseline model.* The baseline model determines the optimal initial capacity adjustment $\Delta K_{CH,0}$ which is restricted as defined by Constraint 4.23f, see Equations 4.23 on page 114. To allow for modular development, $\Delta K_{CH,0}$ is further restricted to 0 units, $\pm e_m$ units or a multiple of $\pm e_m$ units, but within the bounds of $-K_{i,0}$ and $\Delta K_i^{\max}$.
- *Fixed model.* As explained in Section 4.4.1.2, feasible solution candidates of the fixed models are chromosomes that determine the capacity adjustment $\Delta K_{i,t}$ from planning phase t to phase $t+1$. All capacity adjustments that are considered feasible for non-modularised development are described by Constraint 4.24f, see Equations 4.24 on page 116. Thus, in order to allow for modular check-in development in *Evaluation 2*, $\Delta K_{i,t}$ is further restricted to 0 units, $\pm e_m$ units or a multiple of $\pm e_m$ units, but within the bounds of $\pm \Delta K_i^{max}$.
- *CGDRM.* For the CGDRM, the size of capacity adjustments is controlled through parameter θ_1, which ultimately defines by how many units of capacity a system is adjusted by the conditional-go decision rule. Feasible values for θ_1 for non-modularised development are defined in Equation 4.33 on page 125. To allow for modular development of *Check-in 1 and 3*, the set defining feasible values for θ_1 is subsequently further limited to 0 units, $\pm e_m$ units or a multiple of $\pm e_m$ units, but within the bounds of $\pm \Delta K_i^{max}$.
- *RFDRM.* As mentioned in Section 4.4.2.2, feasible capacity adjustment options e_l for the RFDRM are defined in set $e = \{e_1, e_2, \ldots, e_{n_e}\}$. Following the same considerations as for the fixed model and the CGDRM, set e used for the RFDRM is

further limited to 0 units, $\pm e_m$ units or a multiple of $\pm e_m$ units for the evaluation of modular development of *Check-in 1 and 3*, but within the bounds of $\pm\Delta K_i^{max}$.

5.4.3.1 Optimal facility requirements

Table 5.7 summarises the optimal solutions of all the CEP models for modular development of *Check-in 1 and 3* with module sizes in a range of $e_m = 1, 5, 10, 15, \ldots, 35$ check-in desks. The optimal solution of the baseline model is $\Delta K^*_{CH,0} = 28$ desks, irrespective of the module size e_m. In contrast, the optimal solutions of the other CEP models depend on the value of e_m. In case of the fixed model, small values for e_m result in optimal capacity vectors which call for frequent capacity adjustments. In contrast, large values for e_m favour capacity vectors in which capacity is rarely adjusted. The optimal parametrisation $\boldsymbol{\theta}^* = [\theta^*_1, \theta^*_2]$ of the conditional-go decision rule determined with the CGDRM is affected by the value of e_m as well. For $e_m = 1$, the optimal capacity increment θ^*_1 is larger than e_m, while for all other module sizes, the capacity increment θ^*_1 is equal to e_m. Regarding the optimal threshold value θ^*_2, the results suggest that with an increasing value of e_m, θ^*_2 increases too. Finally, the optimal reward function $\mathcal{L}^*$ seems to be dependant on e_m as well. Unfortunately, the identification of patterns is complex. It is noteworthy, however, that all optimal reward functions shown in Table 5.7 consist either of terms $\left(K^s_{CH,t-1} - d^s_{CH,t}\right)$ or $\left(d^s_{CH,t} - K^s_{CH,t-1}\right)$.

The ENPV and VoF of the optimal facility requirements for *Check-in 1 and 3* for *Evaluation 2* are shown in Table 5.8 for module sizes of $e_m = 1, 2, \ldots, 35$ and default parametrisation. The ENPV of facility requirements created with the baseline model do not depend on e_m, while the opposite is true for the ENPV and the VoF of the other models. Each CEP model generates the highest ENPV and VoF at a different value for e^*_m: the fixed model reaches a maximum ENPV of 11 149.80 CHF and VoF of 572.20 CHF at $e^*_m = 15$, the CGDRM achieves a maximum ENPV of 11 190.20 CHF and VoF of 612.50 CHF at $e^*_m = 1$ and $e^*_m = 7$, while the RFDRM results in a maximum ENPV of 11 194.50 CHF and VoF of 616.9 CHF at $e^*_m = 17$. Furthermore, it is worth mentioning that for

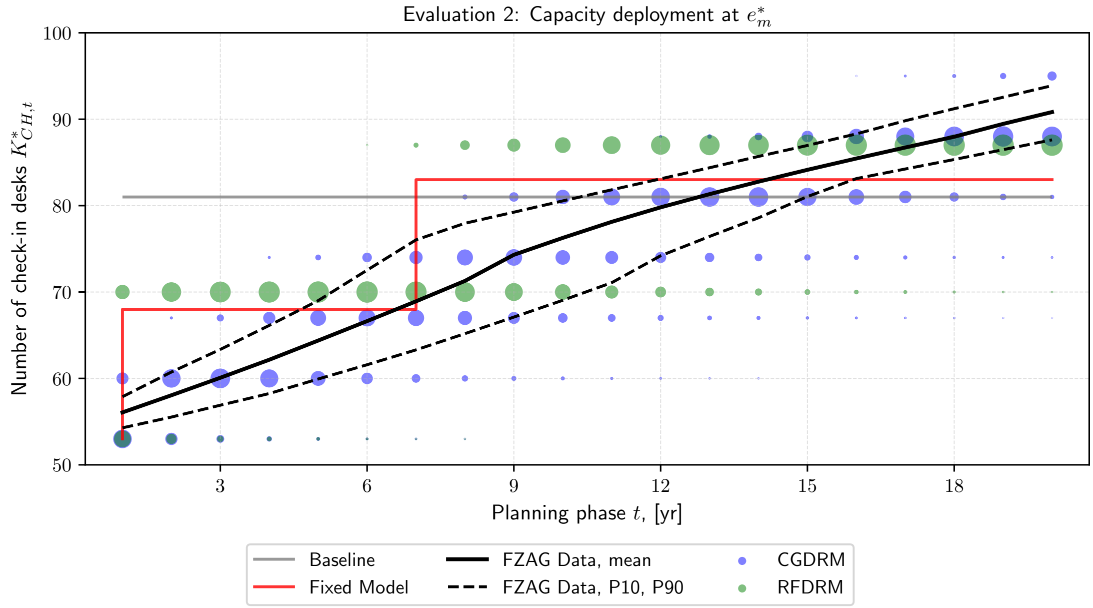

Figure 5.12: Optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 2* at optimal module size e_m^*.

high values of e_m, the ENPV and VoF of the fixed model, the CGDRM and the RFDRM decrease strongly. For detailed numerical results regarding the ENPV, VoF, VaG, VaR and minimum and maximum NPV achieved in *Evaluation 2*, the reader is referred to Table B.2 in Appendix B.

Figure 5.12 depicts the optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 2* at the optimal module sizes[31] e_m^* determined above. The solid lines refer to the capacity deployment sequence of optimal conventional facility requirements, the bubbles to the optimal capacity deployment of flexible facility requirements and the black lines to validation data provided by FZAG. Section 5.4.2 explains in more detail how to read this capacity deployment plot.

[31]For the CGDRM, an optimal module size of $e_m^* = 7$ check-in desks has been selected for Figure 5.12.

e_m	Baseline	Fixed Model	CGDRM	RFDRM
1	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [55, 56, 60, 61, 64, 65, 69, 74, 76, 76, 76, 81, 83, 84, 85, 85, 85, 85, 87, 87]$	$\boldsymbol{\theta}^* = [7, -1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1} \cdot (K^s_{CH,t-1} - d^s_{CH,t})}{CI(e_l) - 2d^s_{CH,t} \cdot (K^s_{CH,t-1} - d^s_{CH,t})}$
5	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 58, 58, 68, 73, 73, 73, 73, 73, 73, 73, 78, 83, 83, 83, 83, 83, 83, 83, 83]$	$\boldsymbol{\theta}^* = [5, -1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1} - d^s_{CH,t} - e_l - CI(e_l) e_l}$
10	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [63, 63, 63, 63, 63, 73, 73, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83]$	$\boldsymbol{\theta}^* = [10, -1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1} + CI(e_l) - 2e_l}{CI(e_l) + d^s_{CH,t}}$
15	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 68, 68, 68, 68, 68, 68, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83]$	$\boldsymbol{\theta}^* = [15, -3]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1} - d^s_{CH,t} + 1}{K^s_{CH,t-1} \cdot (CI(e_l) + d^s_{CH,t} - e_l)}$
20	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 73, 73, 73, 73, 73, 73, 73, 73, 73, 93, 93, 93, 93, 93, 93, 93, 93, 93, 93]$	$\boldsymbol{\theta}^* = [20, -2]$	$\mathcal{L}^* = \frac{d^s_{CH,t} \cdot (K^s_{CH,t-1} - d^s_{CH,t})}{(K^s_{CH,t-1} - e_l) \cdot (K^s_{CH,t-1} + d^s_{CH,t} \cdot (K^s_{CH,t-1} - CI(e_l)))}$
25	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 53, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78, 78]$	$\boldsymbol{\theta}^* = [25, -3]$	$\mathcal{L}^* = \frac{d^s_{CH,t} - K^s_{CH,t-1} + e_l}{CI(e_l)}$
30	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 53, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83, 83]$	$\boldsymbol{\theta}^* = [30, -5]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1} - d^s_{CH,t}}{2d^s_{CH,t} \cdot (CI(e_l) + d^s_{CH,t})}$
35	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [53, 53, 53, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88, 88]$	$\boldsymbol{\theta}^* = [35, -5]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1} - d^s_{CH,t}}{2d^s_{CH,t} \cdot (CI(e_l) + d^s_{CH,t})}$

Table 5.7: Best solution candidates of the baseline model, the fixed model, the CGDRM and the RFDRM for *Evaluation 2* at $\alpha_K = \alpha_A = 0.8$ and $\delta = 0.04$.

5.4.3.2 Simulation results

Figure 5.13 depicts target curves generated with the fixed model, the CGDRM and the RFDRM for *Evaluation 2* and $S = 5000$ scenarios of uncertainty. Each target curve summarises the simulation results for module sizes in a range of $e_m = 1, 2, \ldots, 35$. The simulation results for $e_m = 1$ are displayed with a bold line, while the target curves for $e_m > 1$ are illustrated with thin lines. All target curves whose corresponding ENPVs is larger than or equal to 0.98 times the ENPV of the best performing module size e_m^*, subsequently called $ENPV^{max}$, are coloured in red, green and blue, respectively. In contrast, target curves which lead to an ENPV of less than $0.98 \cdot ENPV^{max}$ are drawn in grey. Additionally, the ENPV of the target curve for $e_m = 1$ is illustrated with a dashed line and $ENPV^{max}$ is indicated with a dash-dotted line.

For the fixed model, the target curve for $e_m = 1$ is to the left of all red-coloured target curves, which indicates that the other coloured target curves, and thus larger module sizes, perform better. The opposite applies for the CGDRM and the RFDRM[32], where with increasing EoS factor values, the very small module sizes are favourable. Furthermore, it is particularly noticeable in Figure 5.13 that for $\alpha_K = \alpha_A = 0.8$ the resulting target curves are situated closer together than for EoS parameter values of 1.

5.4.3.3 Sensitivity analysis

To examine how the results for *Evaluation 2* shown above are affected by variations in a number of parameters, the following sensitivity analyses were conducted: (i) a two-way sensitivity analysis to quantify the impact of the discount rate δ and the EoS parameters α_K and α_A, (ii) a two-way sensitivity analysis to determine how the drift rate μ_D and the volatility parameter σ_D affect the results and (iii) a one-way sensitivity analysis to study the impact of the average service rate μ_K.

[32]For EoS factor values of 0.8 there are a few coloured target curves which perform slightly better than the target curve for $e_m = 1$

e_m	Baseline ENPV	Fixed Model ENPV	VoF	CGDRM ENPV	VoF	RFDRM ENPV	VoF
1	10 577.6	10 760.7	183.1	**11 190.2**	**612.5**	11 126.5	548.9
2	10 577.6	10 828.6	251.0	11 164.8	587.1	11 040.9	463.2
3	10 577.6	10 943.8	366.2	11 165.2	587.6	11 074.7	497.1
4	10 577.6	11 063.0	485.3	11 164.8	587.1	11 123.2	545.6
5	10 577.6	10 952.2	374.6	11 104.9	527.2	11 168.6	591.0
6	10 577.6	11 068.1	490.5	11 164.8	587.1	11 134.5	556.9
7	10 577.6	10 899.1	321.4	**11 190.2**	**612.5**	11 172.6	595.0
8	10 577.6	11 007.6	429.9	11 142.1	564.5	11 109.5	531.9
9	10 577.6	10 982.0	404.4	11 165.2	587.6	11 144.1	566.5
10	10 577.6	11 101.0	523.3	11 080.1	502.5	11 053.7	476.1
11	10 577.6	11 123.4	545.8	11 126.1	548.5	11 048.5	470.9
12	10 577.6	11 020.1	442.5	11 164.8	587.1	11 119.3	541.7
13	10 577.6	10 906.0	328.3	11 084.2	506.5	11 065.5	487.8
14	10 577.6	11 061.8	484.1	10 989.4	411.8	10 966.5	388.9
15	10 577.6	**11 149.8**	**572.2**	10 996.7	419.1	11 037.0	459.4
16	10 577.6	10 964.6	387.0	11 112.4	534.8	10 891.2	313.5
17	10 577.6	11 032.7	455.0	11 160.7	583.1	**11 194.5**	**616.9**
18	10 577.6	10 988.1	410.4	11 139.3	561.7	11 082.9	505.3
19	10 577.6	10 917.9	340.2	11 054.6	476.9	11 025.7	448.1
20	10 577.6	10 822.8	245.1	10 958.6	380.9	10 948.6	370.9
21	10 577.6	10 717.7	140.0	10 865.0	287.4	10 815.5	237.9
22	10 577.6	10 637.3	59.7	10 775.5	197.8	10 753.2	175.6
23	10 577.6	10 560.7	−16.9	10 688.9	111.3	10 661.2	83.6
24	10 577.6	10 538.0	−39.7	10 605.1	27.4	10 457.0	−120.7
25	10 577.6	10 660.8	83.2	10 530.9	−46.8	10 416.3	−161.3
26	10 577.6	10 757.2	179.6	10 459.9	−117.7	10 570.0	−7.6
27	10 577.6	10 827.4	249.7	10 476.7	−101.0	10 714.0	136.3
28	10 577.6	10 872.1	294.4	10 556.8	−20.9	10 636.1	58.4
29	10 577.6	10 891.9	314.2	10 664.6	87.0	10 740.9	163.3
30	10 577.6	10 888.2	310.6	10 770.2	192.5	10 834.8	257.2
31	10 577.6	10 862.3	284.7	10 844.0	266.4	9859.5	−718.1
32	10 577.6	10 826.1	248.4	10 871.8	294.2	10 849.7	272.0
33	10 577.6	10 773.8	196.2	10 852.8	275.2	10 792.0	214.3
34	10 577.6	10 706.8	129.1	10 798.2	220.6	10 713.1	135.5
35	10 577.6	10 627.9	50.2	10 725.7	148.0	10 620.9	43.3

Table 5.8: ENPV and VoF of facility requirements of *Check-in 1 and 3* generated for *Evaluation 2* at $\alpha_K = \alpha_A = 0.8$ and $\delta = 0.04$. All figures are given in CHF.

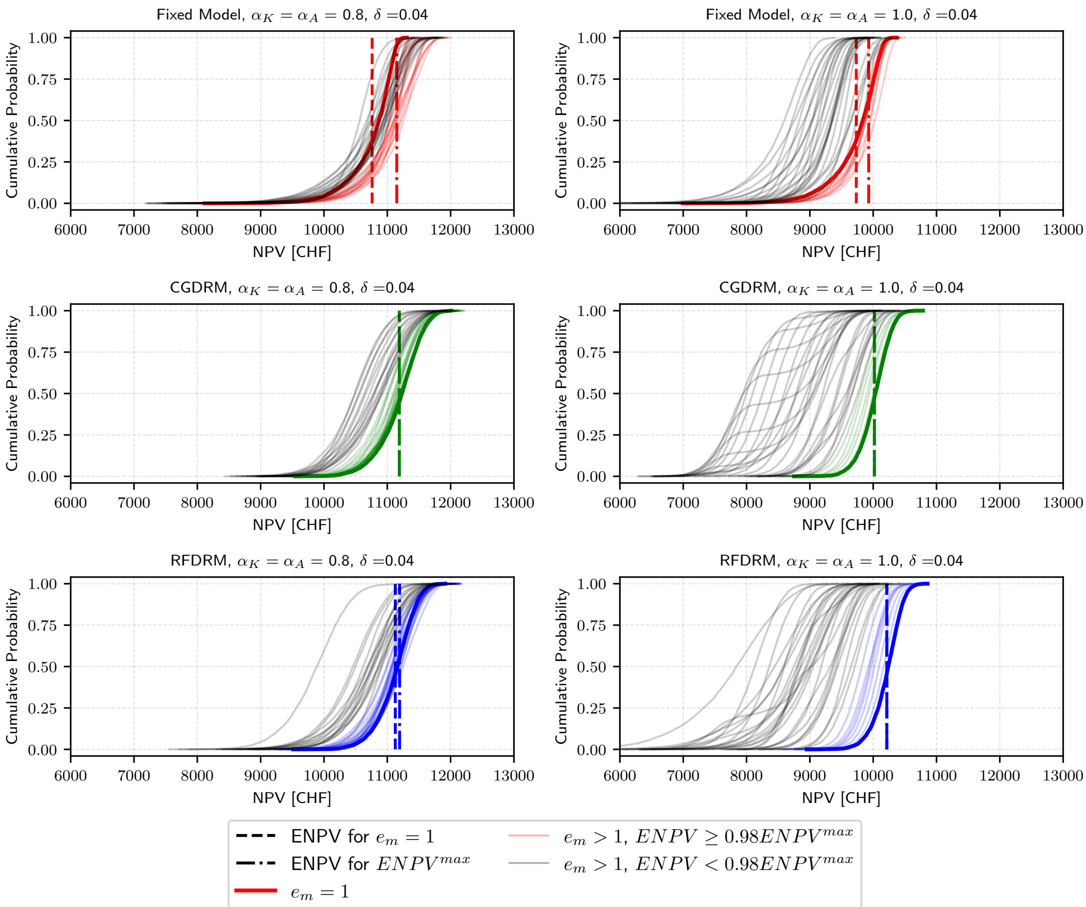

Figure 5.13: Target curves representing simulation results for *Evaluation 2* for module sizes $e_m = 1, \ldots, 35$, EoS parameters $\alpha_K = \alpha_A = 0.8, 1.0$ and a discount rate of $\delta = 0.04$.

Discount rate and EoS parameter. Figure 5.14 shows how EoS parameters values α_K and α_A as well as the discount rate δ affect the ENPV of optimal facility requirements for *Check-in 1 and 3* determined with the fixed model, the CGDRM and the RFDRM for module sizes in a range of $e_m = 1, 2, \ldots, 35$. The CEP models were executed for $\delta = 0.04, 0.12$ and EoS parameter values of $\alpha_K = \alpha_A = 0.7, 0.9, 1$. The observed ENPVs of the fixed model, the CGDRM and the RFDRM models are plotted with red, green and blue dots for $\delta = 0.04$ and similarly coloured triangles for $\delta = 0.12$. The results of the baseline model are indicated with grey dots and triangles. The black dashed lines in each diagram depict smoothed ENPV functions, which were generated with a fitted polynomial of the 7$^{\text{th}}$ degree[33]. Moreover, $ENPV^{max}$ is indicated with a large, coloured diamond. Finally, the area between $ENPV^{max}$ and $0.98 \cdot ENPV^{max}$ is coloured in red, green and blue, respectively.

Data shown in Figure 5.14 suggests that the ENPV of a modular check-in system depends on the value of the EoS parameter. Generally, increasing EoS parameter values, i.e. waning EoS savings, lead to a reduction of the ENPV of the system. Moreover, at low EoS values, the ENPV of the check-in system seems to decrease less quickly in function of an increasing minimum module size e_m. At high EoS parameter values, the ENPV of flexible facility requirements decreases faster and more pronouncedly in function of increasing e_m than that of the conventional facility requirements. Concerning the discount rate δ, Figure 5.14 suggests that higher discount rates lead to a decrease of the ENPVs of *Check-in 1 and 3* and an amplification of the above-mentioned deterioration of the ENPV in function of e_m.

Regarding the VoF, it can be derived from Figure 5.14 that an increase in the EoS parameter value affects the VoF of the facility requirements for $e_m = 1$ and e_m^* in a positive way. For the discount rate δ, a distinction must be made between the results of the fixed model and the flexible CEP models. For the fixed model, the discount rate has a positive influence on the VoF: the higher the discount rate, the higher the VoF. With flexible facility

[33]The fitted polynomial was generated with function *np.polyfit* of the *NumPy* package for the *Python* programming language (Harris et al., 2020).

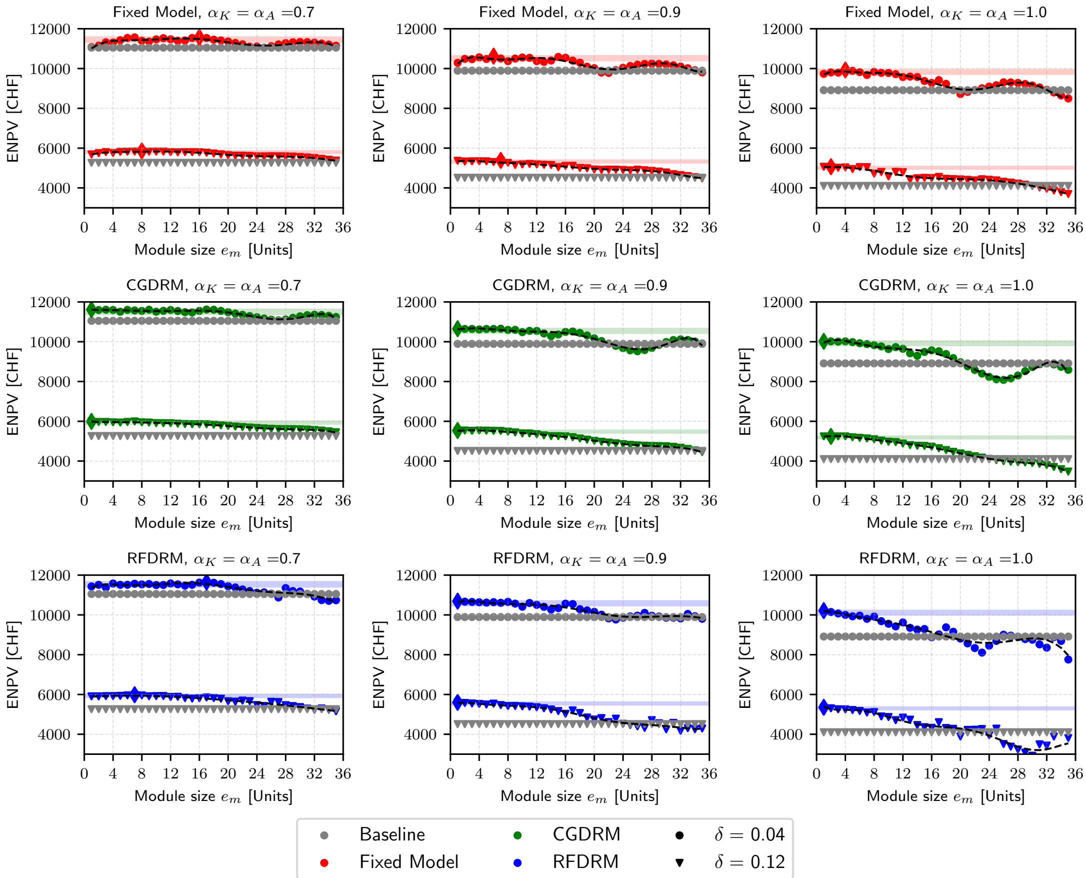

Figure 5.14: ENPV of *Check-in 1 and 3* versus module size e_m for discount rates $\delta = 0.04, 0.12$ and EoS parameter values $\alpha_K = \alpha_A = 0.7, 0.9, 1.0$.

requirements, the VoF is positively influenced by an increase in the discount rate at low EoS parameter values. At high EoS parameter values, however, only the VoF of the CGDRM is positively influenced, while the VoF of the RFDRM is negatively influenced by increasing discount rates. Selected values for $e_m = 1$ and e_m^* can be found in Tables B.2 and B.3 in Appendix B. Furthermore, numerical values for ENPV and VoF occurring at various values of α_K, α_A and δ are presented in Table B.4 in Appendix B.

Percentage drift rate, demand volatility and average service rate. Figure 5.15 depicts how variations in the percentage drift rate μ_D, the demand volatility parameter σ_D and the average service rate μ_K affect the ENPVs of optimal facility requirements created with the fixed model, the CGDRM and the RFDRM for *Evaluation 2*. The diagrams in the left and the centre column of Figure 5.15 contain the results of a two-way sensitivity analysis for drift rates of $\mu_D = 0.04, 0.12$ and demand volatilities of $\sigma_D = 0.04, 0.12$, while diagrams in the right column summarise the resulting ENPV for average service rates of $\mu_K = 50, 60$ and $70\,\mathrm{PAX/h}$.

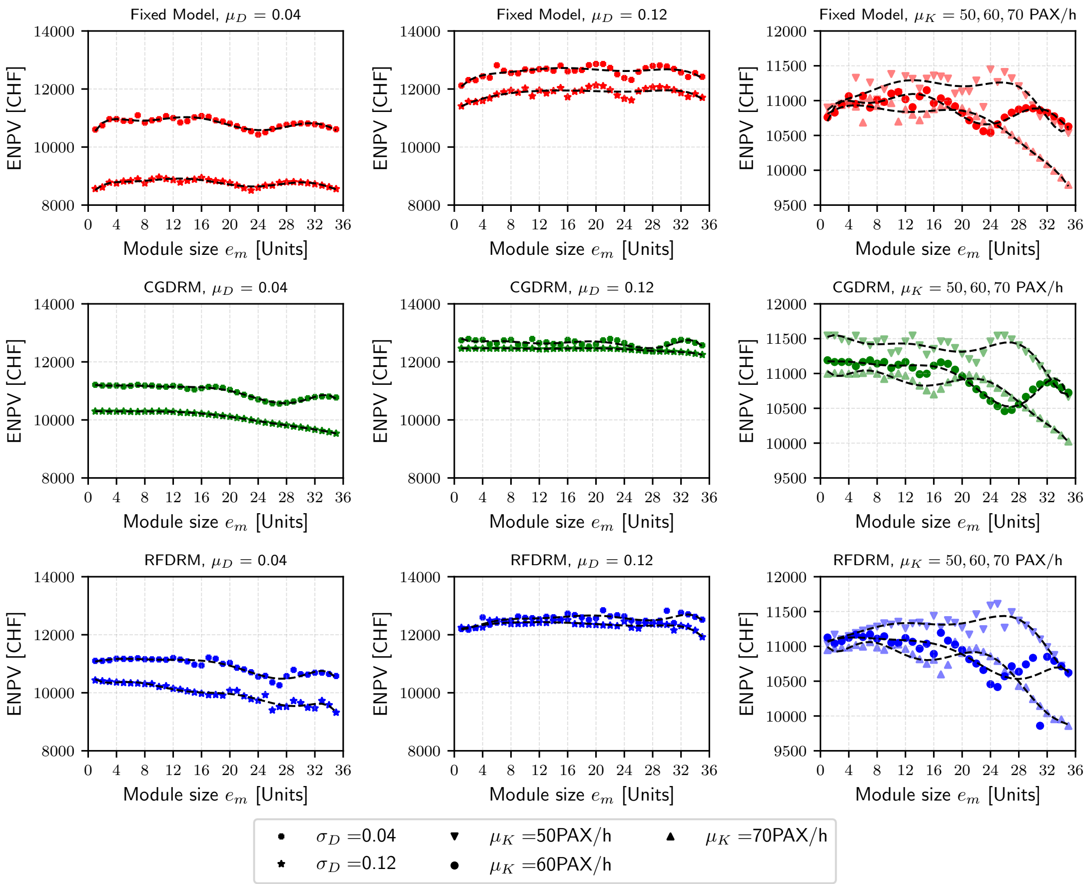

Figure 5.15: Influence of drift rate μ_D, demand volatility σ_D and average service rate μ_K of check-in desk on the ENPV of facility requirements for *Check-in 1 and 3* module sizes in a range of $e_m = 1, 2, \ldots, 35$.

The resulting ENPVs of the fixed model, the CGDRM and the RFDRM show a rather constant behaviour throughout the entire range of e_m for all the tested values of μ_D and σ_D. In line with the results of *Evaluation 1*, higher average demand growth rates result in higher ENPVs of the facility requirements, while higher demand volatility parameter values lead to lower ENPVs. Additionally, the results suggest that flexible facility requirements are less affected by changes in the demand volatility parameter σ_D than conventional ones. Furthermore, demand volatility σ_D seems to influence the results less when the percentage drift rate μ_D is high. The data presented in Figure 5.15 suggests that the VoF of facility requirements depends positively on an increase in the percentage drift rate μ_D. An increase in volatility σ_D for facility requirements created with the fixed model leads to a decrease in VoF, while the opposite is true for flexible facility requirements. Exact numerical values for ENPV and VoF can be found in Table B.5 in Appendix B.

Regarding the impact of the average service rate $\mu_{K,CH}$, results presented in Figure 5.15 suggests that for $e_m = 1, 2, \ldots, 20$, the ENPV of all facility requirements generated are reasonably stable. For $e_m > 20$ check-in desks, however, the ENPV seems to be negatively influenced by increasing values of $\mu_{K,CH}$: ENPV decreases markedly for $\mu_{K,CH} = 50, 70$, while for systems with $\mu_{K,CH} = 60$ a wave-like movement is evident. Regarding the VoF, no clear trends can be identified for facility requirements determined with the fixed model. For flexible facility requirements, however, it can be seen that up to module sizes of approximately $e_m = 20$ the VoF is positively affected by an increase in the service rate, while the opposite is the case for $e_m > 20$. Exact numerical values for ENPV and VoF can be found in Table B.6 in Appendix B.

5.4.4 Evaluation 3 – Buffer space

To evaluate the buffer space option for *Check-in 1 and 3*, the CEP models do not require to be adjusted, but are executed using the same configuration as in *Evaluation 1*. While for *Evaluation 1*, the available buffer space has been set to $0\,\mathrm{m}^2$, the total size of the buffer space available for *Evaluation 3* is controlled by means of two parameters: (i) the size of the buffer space which is already available at $t = 0$, i.e. the buffer size identified in the inventory, and (ii) the size of the buffer space, which is purposely built or allocated at $t = 0$. Please note that the CEP models used in this study do not allow for the construction of additional buffer space for all planning periods after $t = 0$. As defined in the inventory, *Check-in 1 and 3* are currently not equipped with buffer spaces. Thus, the size of the buffer space is controlled exclusively through parameter $A_{R,CH,0}$, which defines the buffer space installed at $t = 0$. As buffer spaces have to be built in such a way that they can be connected with the BHS at a later date, the installation costs per square metre of buffer space are 20 % higher than the unit installation costs of regular terminal space. Moreover, buffer space come with unit operating costs for maintenance and cleaning of $co_R = 0.05\,\mathrm{CHF}/\,\mathrm{m}^2/\,\mathrm{h}$. For an overview on all parameters applied, the reader is referred to Appendix A.

Concerning the generation of revenues by means of buffer spaces, *Evaluation 3* considers two distinct cases: (i) the installation of buffer space which remains unused until it is transformed into a check-in facility, and (ii) the installation of buffer space, which is temporarily used for the provision of retail, food and beverage services, until it is transformed into a check-in facility. For the first case, the average revenue generated by one square meter of buffer space $r_{R,CH}$ is $0\,\mathrm{CHF}/\,\mathrm{m}^2/\,\mathrm{h}$, while for the second case, FZAG assumes average retail revenues of $r_{R,CH} = 0.652\,\mathrm{CHF}/\,\mathrm{m}^2/\,\mathrm{h}$, see Appendix A.

5.4.4.1 Optimal facility requirements

Optimal solutions of the fixed model, the CGDRM and the RFDRM for *Check-in 1 and 3* and *Evaluation 3* are summarised in Tables 5.9 and 5.10 for a number of different values of buffer size $A_{R,CH,0}$. Table 5.9 contains the results for buffer space which is not utilised for retail purposes, while Table 5.10 summarises optimal facility requirements for facilities in which the buffer is temporarily used for retail. Irrespective of whether the buffer space is utilised for retail or not, the optimal solution of the baseline model is $\Delta K^*_{CH,0} = 28$ desks. For the other CEP models, however, the optimal solutions depend on $A_{R,CH,0}$. For conventional facility requirements created with the fixed model, differences between check-in facilities containing buffers with retail utilisation versus buffers without retail utilisation are evident. For systems that have a large buffer space with retail utilisation, the capacity of *Check-in 1 and 3* is expanded less throughout the entire planning horizon than for systems that have an equally large buffer space without retail utilisation. For example, if $3000\,\mathrm{m}^2$ buffer space is created in *Check-in 1 and 3*, the capacity at the end of the planning horizon for a system in which the buffer is used on a temporary basis for the provision of retail services is 84 desks, while the capacity in a system whose buffer is not used for retail services is 93 desks.

The optimal parametrisation $\boldsymbol{\theta}^* = [\theta_1^*, \theta_2^*]$ of the conditional-go decision rule determined with the CGDRM for *Evaluation 3* depends on the utilisation of the buffer space. Regarding capacity increment parameter θ_1, the magnitude of θ_1^* is positively influenced by an increasing size of a buffer which is not used for retail services, while θ_1^* is negatively affected by larger buffer spaces temporarily used for retail purposes. The optimal value of threshold parameter θ_2^* is reduced for both buffer types with increasing buffer sizes. Interestingly, for a system containing a buffer with retail utilisation, the optimal value of parameter θ_2^* is slightly lower than for a system with a buffer without retail utilisation. In terms of the optimal reward function $\mathcal{L}^*$ determined with the RFDRM, no patterns and dependencies can be identified. As such, the optimal reward function terms determined for *Evaluation 3* appear to be less complex than the ones identified for *Evaluation 2*. Further, it is noticeable that function $\frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$ was determined as optimal decision rule for both systems containing buffer spaces with and without temporary retail utilisation for a number of different initial buffer size values.

An overview of the achieved ENPV and VoF of all the CEP models for buffer spaces of size $0\,\mathrm{m}^2$, $750\,\mathrm{m}^2$, $1500\,\mathrm{m}^2$ and $3000\,\mathrm{m}^2$ can be found in Table 5.11.

$A_{R,CH,0}$	Baseline	Fixed Model	CGDRM	RFDRM
$0\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,59,60,65,65,66,70,74,75,80,$ $80,85,85,86,87,87,87,87,91,91\,]$	$\boldsymbol{\theta}^* = [7,-1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$
$500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,59,65,66,66,67,69,73,81,81,$ $81,86,86,87,88,88,88,88,90,90\,]$	$\boldsymbol{\theta}^* = [7,-1]$	$\mathcal{L}^* = \frac{{K^s_{CH,t-1}}^2}{K^s_{CH,t-1}\left(K^s_{CH,t-1}-d^s_{CH,t}+e_l\right)-CI(e_l)}$
$1000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,60,60,61,66,66,67,69,73,74,79,$ $79,84,84,85,86,86,86,86,90,90\,]$	$\boldsymbol{\theta}^* = [7,-1]$	$\mathcal{L}^* = \frac{{K^s_{CH,t-1}}^2}{K^s_{CH,t-1}\left(K^s_{CH,t-1}-d^s_{CH,t}+e_l\right)-CI(e_l)}$
$1500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,57,60,61,66,66,67,70,74,82,82,$ $82,87,87,88,89,89,89,89,93,93\,]$	$\boldsymbol{\theta}^* = [18,-2]$	$\mathcal{L}^* = \frac{{K^s_{CH,t-1}}^2}{K^s_{CH,t-1}\left(K^s_{CH,t-1}-d^s_{CH,t}+e_l\right)-CI(e_l)}$
$2000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,60,61,63,66,67,71,75,80,80,$ $80,85,85,86,87,87,87,87,89,89\,]$	$\boldsymbol{\theta}^* = [19,-1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{2K^s_{CH,t-1}-2d^s_{CH,t}-e_l}$
$2500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,60,61,63,66,67,71,75,80,80,$ $80,85,85,86,87,87,87,87,89,89\,]$	$\boldsymbol{\theta}^* = [18,-2]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$
$3000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,60,64,66,69,70,74,79,80,80,$ $80,85,85,86,91,91,91,91,93,93\,]$	$\boldsymbol{\theta}^* = [18,-2]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$

Table 5.9: Best solution candidates of the baseline model, the fixed model, the CGDRM and the RFDRM for facility requirements of *Check-in 1 and 3* containing buffer space without retail utilisation.

$A_{R,CH,0}$	Baseline	Fixed Model	CGDRM	RFDRM
$0\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,59,59,60,65,65,66,70,74,75,80,$ $80,85,85,86,87,87,87,87,91,91\,]$	$\boldsymbol{\theta}^* = [7,-1]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$
$500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,55,56,57,59,63,64,72,77,78,78,$ $78,83,83,84,85,85,85,85,87,87\,]$	$\boldsymbol{\theta}^* = [6,-2]$	$\mathcal{L}^* = \frac{1}{K^s_{CH,t-1}-d^s_{CH,t}}$
$1000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,55,56,57,59,59,60,60,68,77,77,$ $77,82,82,83,84,84,84,84,87,87\,]$	$\boldsymbol{\theta}^* = [6,-3]$	$\mathcal{L}^* = \frac{K^s_{CH,t-1}}{K^s_{CH,t-1}-d^s_{CH,t}}$
$1500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,55,56,57,58,58,60,63,68,71,71,$ $71,72,79,80,81,81,81,81,84,84\,]$	$\boldsymbol{\theta}^* = [5,-3]$	$\mathcal{L}^* = \frac{-CI(e_l)d^s_{CH,t}}{K^s_{CH,t-1}-d^s_{CH,t}}$
$2000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,55,56,57,59,59,60,64,72,73,73,$ $74,75,75,76,81,81,81,81,84,84\,]$	$\boldsymbol{\theta}^* = [5,-3]$	$\mathcal{L}^* = \frac{{e_l}^2}{d^s_{CH,t}-K^s_{CH,t-1}+1}$
$2500\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,53,54,58,59,59,63,67,72,73,73,$ $74,75,76,77,78,78,78,79,81,81\,]$	$\boldsymbol{\theta}^* = [5,-3]$	$\mathcal{L}^* = \frac{{e_l}^2}{d^s_{CH,t}-K^s_{CH,t-1}+1}$
$3000\,\mathrm{m}^2$	$\Delta K^*_{CH,0} = 28$	$\mathbf{K}^*_{CH} = [\,55,56,57,58,58,60,64,69,70,70,$ $70,71,78,79,80,80,80,80,84,84\,]$	$\boldsymbol{\theta}^* = [5,-3]$	$\mathcal{L}^* = \frac{{e_l}^2}{d^s_{CH,t}-K^s_{CH,t-1}+1}$

Table 5.10: Best solution candidates of the baseline model, the fixed model, the CGDRM and the RFDRM for facility requirements of *Check-in 1 and 3* containing buffer space with retail utilisation.

Buffer	Model	Without retail utilisation ENPV	Without retail utilisation VoF	With retail utilisation ENPV	With retail utilisation VoF
0 m^2	Baseline	10 525.7		10 525.7	
	Fixed Model	10 602.8	77.1	10 602.8	77.1
	CGDRM	**11 210.8**	**685.1**	**11 210.8**	**685.1**
	RFDRM	11 099.7	574.0	11 099.7	574.0
750 m^2	Baseline	10 016.0		16 662.9	
	Fixed Model	10 564.2	548.2	12 769.8	–3893.1
	CGDRM	**10 986.2**	**970.2**	13 271.2	–3391.7
	RFDRM	10 890.3	874.3	**13 347.7**	**–3315.2**
1500 m^2	Baseline	9380.4		22 674.2	
	Fixed Model	10 066.3	685.9	17 581.1	–5093.0
	CGDRM	**10 645.8**	**1265.5**	18 181.5	–4492.6
	RFDRM	10 464.0	1083.6	**18 181.6**	**–4492.5**
3000 m^2	Baseline	8026.3		34 613.8	
	Fixed Model	8815.2	788.9	29 563.4	–5050.4
	CGDRM	**9357.0**	**1330.7**	30 163.5	–4450.3
	RFDRM	9149.3	1123.0	**30 166.5**	**–4447.3**

Table 5.11: ENPV and VoF of *Check-in 1 and 3* for *Evaluation 3* and buffer space with and without retail utilisation. All ENPV and VoF figures are provided in CHF.

The optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 3* are illustrated in Figure 5.16 for buffer space without retail utilisation and in Figure 5.17 for buffer space with temporary retail utilisation. The solid lines refer to the capacity deployment sequence of optimal conventional facility requirements, the bubbles to the optimal capacity deployment of flexible facility requirements and the black lines to validation data provided by FZAG. Section 5.4.2 explains in more detail how to read this capacity deployment plot.

5.4.4.2 Simulation results

Figure 5.18 depicts target curves of stochastically optimal flexible and conventional facility requirements for *Check-in 1 and 3* and *Evaluation 3* determined with the fixed model, the CGDRM and the RFDRM. The diagrams in the left column of the figure summarise the results for a percentage drift rate of $\mu_D = 0.04$, while in the right column, res-

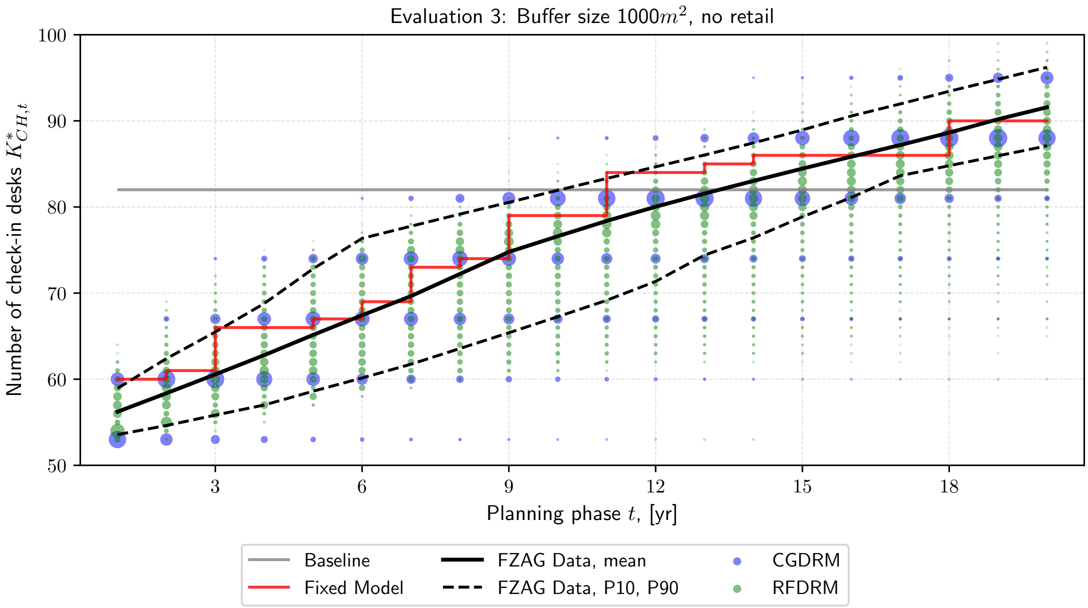

Figure 5.16: Optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 3* for buffer size of $A_{R,CH,0} = 1000\,\mathrm{m}^2$ in which no retail services are provided.

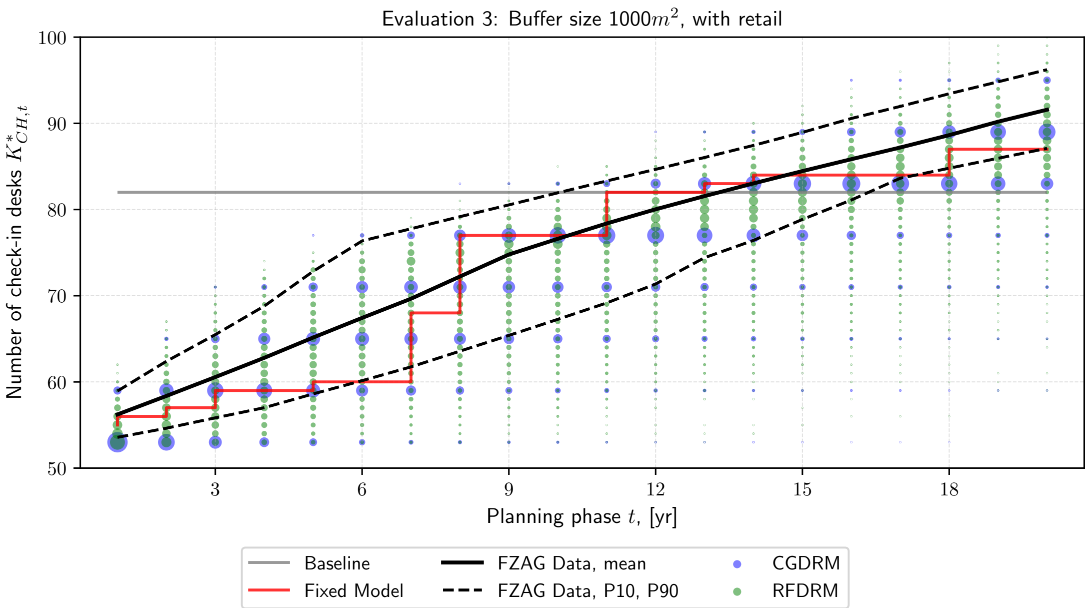

Figure 5.17: Optimal capacity deployment sequences for *Check-in 1 and 3* and *Evaluation 3* for buffer size of $A_{R,CH,0} = 1000\,\mathrm{m}^2$ in which temporary retail services are provided.

ults for $\mu_D = 0.12$ are shown. The first row of diagrams depicts the results for a buffer space of $A_{R,CH,0} = 0\,\mathrm{m}^2$, the second row for $A_{R,CH,0} = 750\,\mathrm{m}^2$ and the third row for $A_{R,CH,0} = 1500\,\mathrm{m}^2$. Target curves plotted as thin lines show results for buffer without retail utilisation, while bold lines illustrate results for buffer space with retail utilisation.

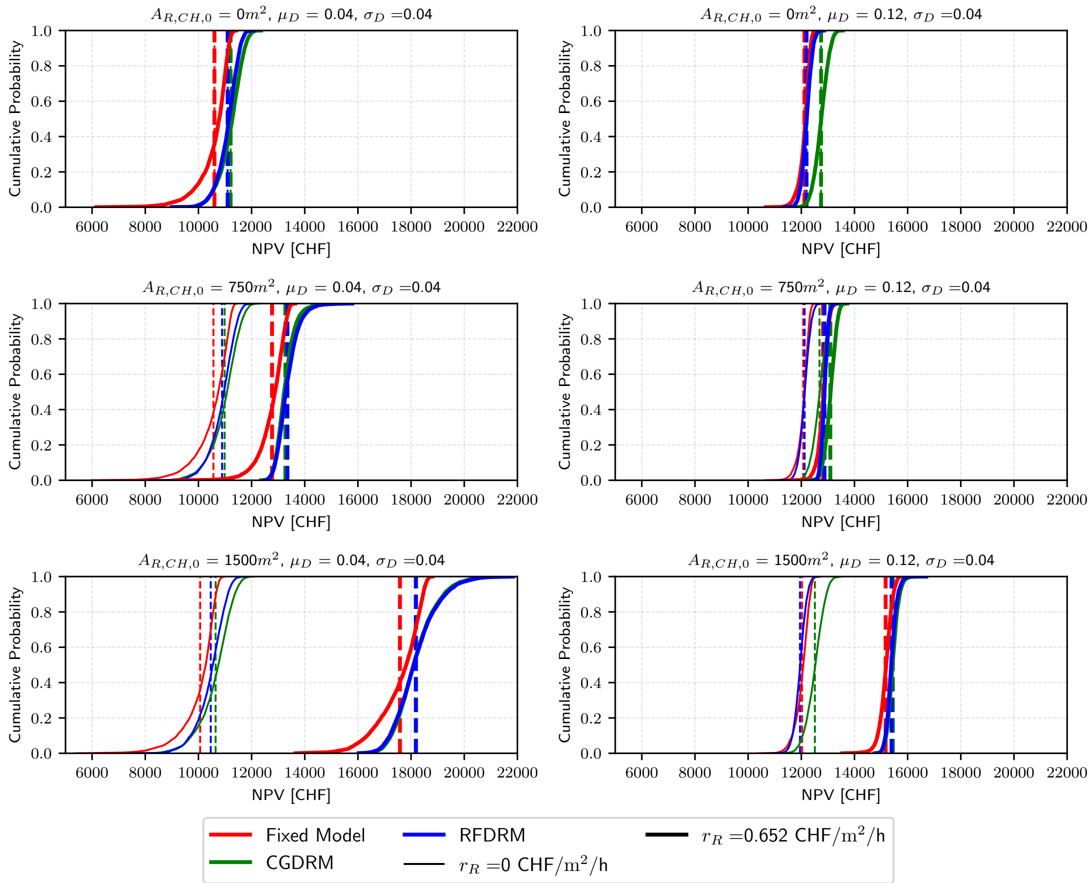

Figure 5.18: Simulation results for *Check-in 1 and 3* and *Evaluation 3* for buffer of size $A_{R,CH,0} = 0, 750, 1500\mathrm{m}^2$, in which no retail services are provided (left column) and in which retail services are provided (right column).

As illustrated in Figure 5.18 and summarised in Table B.7 (see Appendix B), the ENPV of *Check-in 1 and 3* appears to depend on the size of the initially allocated buffer space $A_{R,CH,0}$, the percentage drift rate μ_D and on whether the provision of temporary retail services is permitted or not. Generally, flexible facility requirements lead to higher ENPVs than facility requirements determined with the fixed model. Moreover, for facilities in which buffer space cannot be used for the provision of temporary retail services, the ENPV of the system is reduced with increasing buffer size. This effect is also clearly noticeable in Figure 5.19. In contrast, if retail is allowed, the ENPV of the system is positively affected by an increasing buffer size. As illustrated in Figure 5.19, the ENPV functions of all the CEP models but the baseline model can be divided into two distinct sections: a section in which the ENPV of facility requirements increase only slightly and a section in which the ENPV increases almost linearly with the buffer size. The transition between these sections occurs at buffer sizes of approximately $A_{R,CH,0} = 1000\,\mathrm{m}^2$ for $\mu_D = 0.04$ and $A_{R,CH,0} = 2000\,\mathrm{m}^2$ for $\mu_D = 0.12$, respectively. The ENPV of the baseline model appears to increase linearly in function with the buffer size. Furthermore, it can also be seen in Figure 5.18 that at high percentage drift rates μ_D, the difference between the ENPV of a system in which the buffer is used for the provision of retail services and a system in which the buffer space is not utilised for the provision of retail services is less pronounced than for low percentage drift rates. Exact numerical values concerning Figure 5.18 can be found in Table B.7 in Appendix B.

5.4.4.3 Sensitivity analysis

To examine how the results for *Evaluation 3* shown above are affected by variations in a number of parameters, three different sensitivity analyses were conducted: (i) a two-way sensitivity analysis to determine how the percentage drift rate μ_D and the demand volatility parameter σ_D affect the results, (ii) a two-way sensitivity analysis to quantify the impact of the discount rate δ and EoS parameters α_K and α_A, as well as (iii) a one-way sensitivity analysis to study the impact of the average service rate μ_K.

Percentage drift rate and demand volatility. Figure 5.19 shows how the percentage drift rate μ_D and the demand volatility parameter σ_D affect the ENPV of facility requirements for *Check-in 1 and 3* determined with the fixed model, the CGDRM and the RF-DRM for different buffer space sizes in a range of $A_{R,CH,0} = 0, 500, \ldots 3500\mathrm{m}^2$. For buffer space which does not allow for the provision of temporary retail services, the ENPV is positively affected by an increase in the percentage drift rate of demand μ_D, while the opposite applies for an increase in the volatility of demand σ_D. For facilities in which the buffer space can be temporarily used for retail purposes, the ENPV is negatively affected by both an increase in the drift rate μ_D and in the demand volatility parameter σ_D.

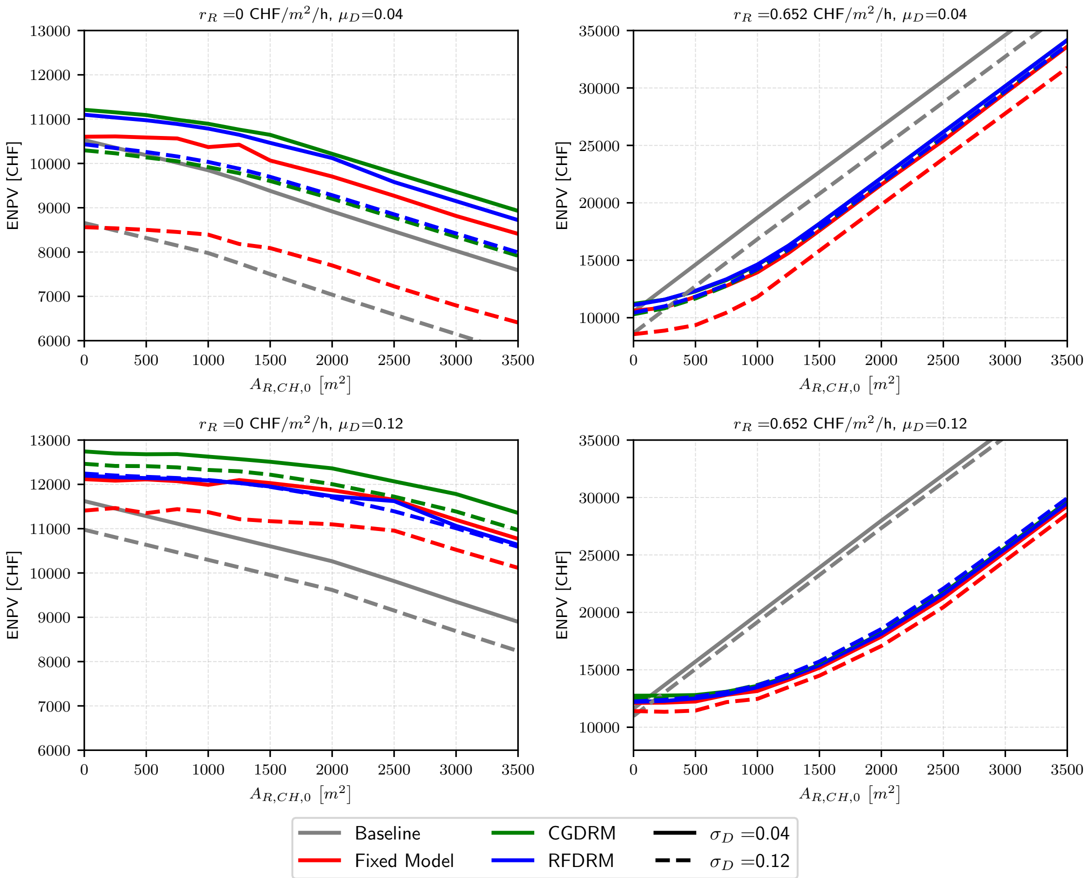

Figure 5.19: Influence of average retail revenue $r_{R,CH}$, percentage drift rate μ_D and demand volatility σ_D on the ENPV for *Check-in 1 and 3* and *Evaluation 3*. Results for buffer space without retail utilisation are depicted in the diagrams in the left column, while results for buffer space with retail utilisation are shown in the right column of diagrams.

The results shown in Figure 5.19 suggest that the VoF of a system with buffer space without retail utilisation is positively influenced by an increase in the percentage drift rate μ_D, while the opposite is true for a buffer with retail utilisation. Furthermore, it can be seen that for buffer spaces without retail utilisation, the VoF of conventional facility requirements determined with the fixed model is negatively influenced by an increase in demand volatility σ_D, while the opposite is true for flexible facility requirements. For buffer spaces with retail utilisation, an increase in volatility leads to an increase in VoF for the majority of all facility requirements generated[34]. The exact ENPV and VoF figures can be found in Table B.7 in Appendix B.

Discount rate, EoS parameter and average service rate. The impact of variations in the discount rate δ, the EoS parameters α_K and α_A as well as the average service rate of a check-in desk $\mu_{K,CH}$ on the ENPV of both flexible and conventional facility requirements for *Check-in 1 and 3* is presented in Figure 5.20. The sensitivity of the models to variations in δ, α_K and α_A is shown in the diagrams in the left and middle columns of Figure 5.20, while the CEP models' dependence on changes in $\mu_{K,CH}$ are depicted in the diagrams in the right column. Moreover, the top row of diagrams presents the data for buffer space which is not temporarily used for retail purposes, while the bottom row of diagrams summarises the results for buffer space where temporary retail services are provided.

An increase in the discount rate δ affects the ENPV of *Check-in 1 and 3* negatively, irrespective of whether the buffer space allows for the provision of temporary retail services or not. With increasing buffer space size, however, the negative influence of an increasing discount rate is reduced. An increase in EoS parameters values α_K and α_A, i.e. waning EoS effects, have a negative effect on the ENPV of optimal facility requirements for *Check-in 1 and 3* which have buffer spaces. With regard to the VoF, it can be seen that an increase in the EoS parameter value leads to an increase in the VoF. The influence of the discount rate δ on the VoF depends on the buffer type: for buffer spaces that do not permit retail utilisation, an increase in the discount rate δ leads to a decrease of the VoF, while the opposite is the case for buffer space with retail utilisation. Exact ENPV and VoF figures can be found in Table B.8 in Appendix B.

Finally, the ENPV of facility requirements for *Check-in 1 and 3* seems to depend

[34] An increase in demand volatility σ_D affects the VoF of facility requirements determined with the fixed model slightly negative for small buffer space sizes.

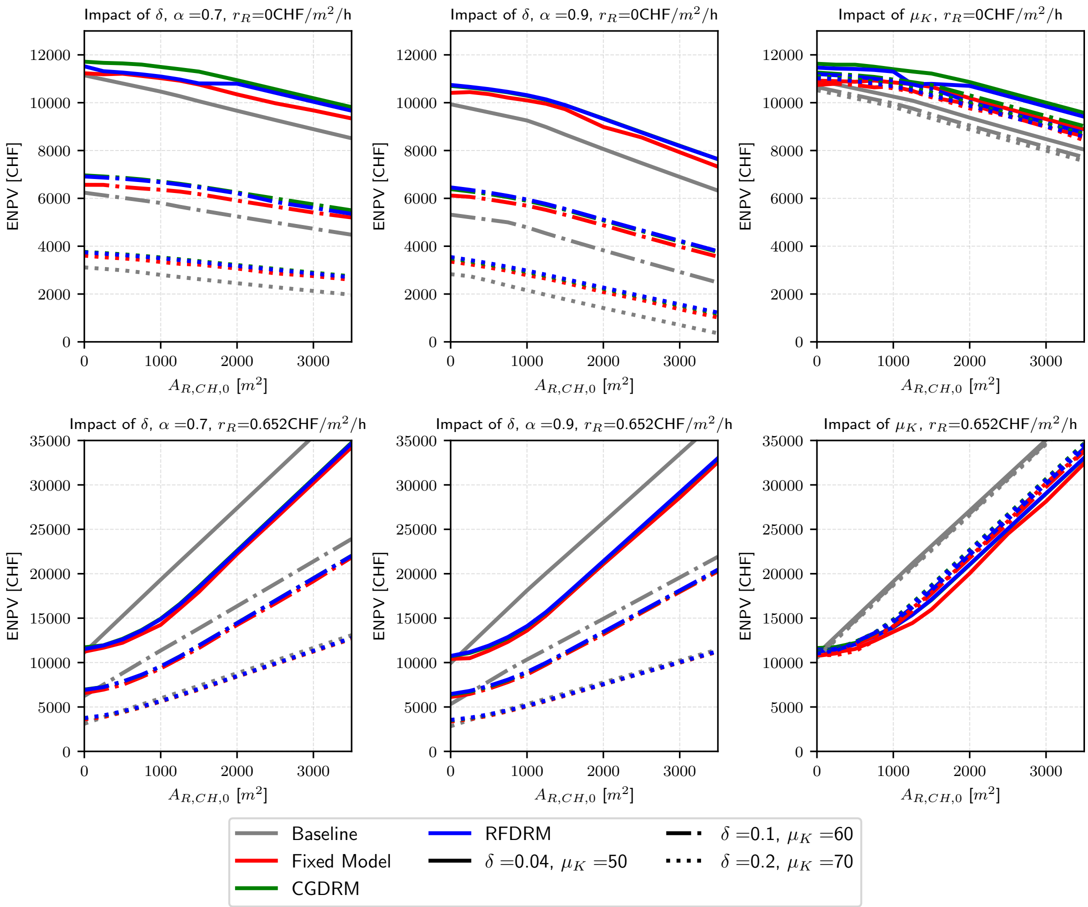

Figure 5.20: Influence of the discount rate δ and the EoS parameters α_K and α_A (left and centre column) as well as the service rate $\mu_{K,CH}$ (right column) on the ENPV of *Check-in 1 and 3* for *Evaluation 3*.

only very weakly on changes in the service rate $\mu_{K,CH}$. To this end, for buffer spaces without retail utilisation, an increasing service rate leads to a slight decrease in ENPV, while the opposite is true for buffer spaces with retail utilisation. Moreover, it can be seen that for systems that contain a buffer space without retail utilisation, the VoF of conventional facility requirements increase with increasing service rates $\mu_{K,CH}$, while the opposite applies for flexible facility requirements. For facilities that have a buffer space with retail utilisation, an increase in the service rate leads to an increase in VoF. Exact ENPV and VoF figures can be found in Table B.9 in Appendix B.

5.5 Solution performance

The GAs used for the near-optimal solution of the fixed model and the CGDRM, as well as the GEP applied for the RFDRM belong to the class of *evolutionary optimization algorithms*, in which the optimal solution to a problem is approximated in an iterative procedure over the course of a number of generations. As soon as the termination conditions of the GA and GEP are reached, the best available solution at that time is designated as the *near-optimal solution* of the optimization problem at hand.

In practical applications, users have to determine for how many generations an evolutionary algorithm should be executed. In this way, a trade-off must be found between the required solution time and the accuracy of the solution. If the algorithm is terminated too early, the near-optimal solution obtained is very likely to be of poor quality. However, if the algorithm is terminated too late, there is a good chance that a considerable amount of computing time will be invested without substantially improving the quality of the solution. Consequently, the solution procedure should be carried out as often as necessary to determine a sufficiently accurate solution, but as little as possible to save computing time.

The left diagram in Figure 5.21 depicts how the ENPV of the best solution candidate for *Evaluation 1* is improved over the number of generations g of the GA applied for the fixed model, the CGDRM and GEP used by the RFDRM. The right diagram in Figure 5.21 illustrates the computing time required to reach a certain number of generations g. For the data shown in Figure 5.21, all the CEP models were provided with 5000 demand scenarios as well as default parametrisation, as defined in Appendix A. Furthermore, the CEP models were solved in 5 independent simulation runs on an *27" iMac* from the year 2017 with a 4.2 GHz *quad core Intel core i7* processor and 32 GB RAM. Consequently, the data shown in Figure 5.21 are average values over the 5 simulation runs.

Concerning the solution convergence of the CEP models, the data depicted in Figure 5.21 suggests that the CGDRM and the RFDRM requires approximately 20 and 50

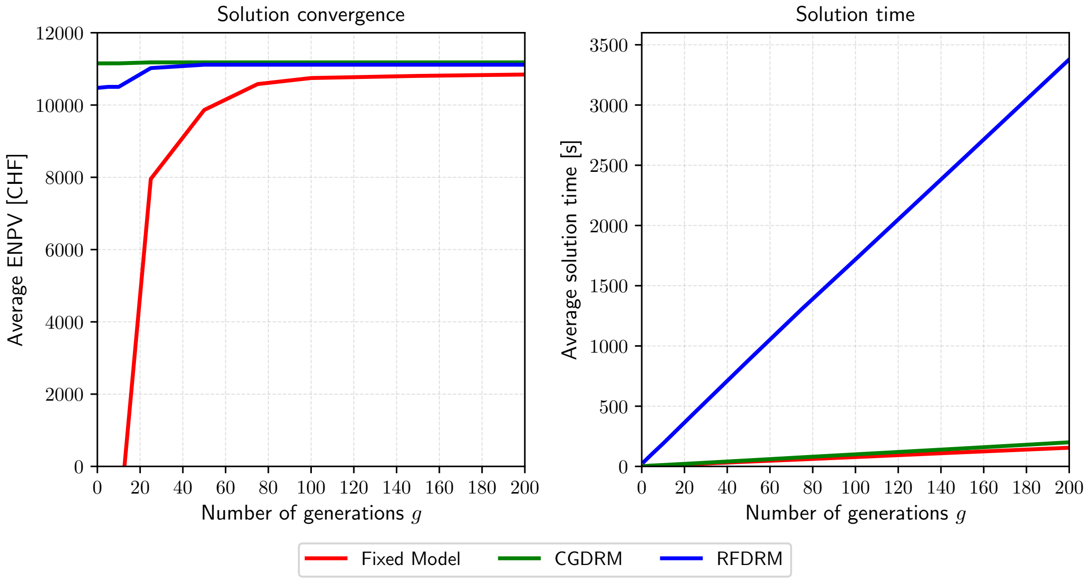

Figure 5.21: Solution convergence (left) and time required to acquire solution (right) of the fixed model, the CGDRM and the RFDRM. All results are average values over 5 independent runs of the solvers generated for *Evaluation 1*.

generations, respectively, to converge to a stable solution[35]. The solution of the fixed model is stable after roughly 100 generations. Regarding the time required to achieve a near-optimal solution, the fixed model and the CGDRM show similar results: the fixed model requires on average 77.5 s to process 100 generations and 154.8 s for 200 generations, while the CGDRM requires on average 100.3 s and 200.6 s, respectively. In contrast, the RFDRM takes on average 1718.6 s for 100 generations and 3378.8 s for 200 generations.

[35]For this study, a stable solution is assumed if the relative change of the ENPV of the best performing solution candidate from generation g to generation $g+1$ is less than 0.1 %. Please note that the literature often applies significantly smaller values to define *stagnation*. For instance, Kramer (2017) suggests to terminate a genetic algorithm if the relative improvement of the fitness value of the best chromosome from population g to population $g+1$ is less than 10^{-8}. However, it was decided that by choosing a relatively large value to define stagnation, the solution time can be positively influenced, while the solution quality is still acceptable for an application in the context of ASP.

Chapter 6

Discussion

This chapter discusses both the methods presented in Chapter 4 as well as the planning example introduced in Chapter 5. To this end, the discussion is organised as follows: Sections 6.1, 6.2 and 6.3 discuss the research areas 1, 2 and 3, respectively. The implications of this study are outlined in Section 6.4.

6.1 Research area 1 – Demand models

Research area 1 is concerned with the demand module, which consists of models used to create annual aggregated passenger demand scenarios by means of GBM as well as the conversion of these scenarios into airport passenger terminal facility-specific DHL demand vectors. For this purpose, two models were developed in this study, namely the annual aggregated demand model and the DHL demand model, which are each discussed below.

6.1.1 Annual aggregated demand model

The annual aggregated demand model enables airport planners to create large numbers of scenarios describing future annual aggregated passenger demand for an airport and therefore provides answers to research question RQ1. The GBM-based methodology proposed in this study has proven to be very effective, computationally efficient and straightforward to apply in practice. Moreover, the suggested method does not require any special software, as it could also be implemented in a spreadsheet. The scenarios created with the annual aggregated demand model for ZRH Airport correspond to initial expectations and are comparable with similar results presented in the literature on flexible engineering systems (Cardin & Hu, 2016; Cardin et al., 2015; Cardin, Xie et al., 2017; De Weck et al., 2007; Geltner & De Neufville, 2018; Hu et al., 2018; Hu et al., 2020; Hu & Guo, 2019; Mun, 2002). Without major adaptations, the model presented in this study could also be used for the generation of scenarios for other factors subject to uncertainty in the context of ASP, such as the number of future ATMs per year or future aggregated annual freight volumes.

At this point, it must be pointed out that the GBM-based annual aggregated demand model is rather simplistic, since it is based exclusively on past passenger volume observations and does not take into account any other factors influencing demand. For this reason, it cannot replace the already well-established methods used to generate demand forecasts for airports, such as time series or trend extrapolations (Doganis, 2013; Kazda & Caves, 2007; Vasigh et al., 2018), consensus forecasts, market share forecasts (Eurocontrol, 2018; Federal Aviation Administration [FAA], 2021) or econometric forecasts (Chen, Chang et al., 2009; De Neufville et al., 2013; Kazda & Caves, 2007; Profillidis, 2000). However, a GBM-based model would be able to complement the above-mentioned forecasting methods by facilitating the creation of large numbers of demand forecast scenarios. For example, a GBM-based model could have been used to create demand scenarios for the Madrid *Barajas* Airport master planning example introduced in Chapter 1. In this example, instead of creating just three scenarios, airport planners could have created a large number of different demand scenarios with a small workload. Thus, the annual aggregated demand mode presented in this study is a tool that can be perfectly integrated into the methods and planning processes already used at airports today.

GBM-based models have certain limitations in terms of (i) their parameters, (ii) assumptions regarding the distribution of the input data and (iii) the missing capacity to represent jumps in the variable which is to be modelled. Regarding the estimation of the parametrisation of GBM-based models, the literature recommends using the largest possible dataset of historical observations of the variable to be modelled. As mentioned in Section 4.1, Croghan et al. (2017) suggest at least 100 or even better 1000 historical observations of the variable in question should be examined. For the generation of annual aggregated demand scenarios of airports, however, this requirement is impossible to meet, due to a lack of available data. In this study, demand observations from 11 consecutive years are used to parametrise the annual aggregated demand model. At first glance, this data basis appears to be rather limited. However, when compared with similar studies mentioned in the literature on flexible engineering systems, such as Cardin and Hu (2016), Cardin, Xie et al. (2017) and Hu et al. (2018), Hu et al. (2020), it is noticeable that these works are limited in a similar way. In addition, the standard errors for the drift rate and volatility estimated in this study are 0.814 % and 0.603 %, respectively, which is acceptable[36]. Thus, it is assumed that the approach chosen in this study is viable as long as practitioners are aware of the fact that their planning is founded on a limited data basis.

GBM further assumes that both the percentage drift rate μ and the percentage volatility σ of the variable to be modelled are constant. Although this assumption allows for the postulation of relatively simple models, it might not be appropriate for all types of applications. Especially the volatility parameter σ is often subject to variations in function of time as well as other micro-economic or macro-economic variables. In this regard, an example relevant to ASP is presented by Marathe and Ryan (2005), who show that the volatility of airline passenger data is time dependent due to cyclical and seasonal demand patterns. In order to model time-dependent volatility, the use of so-called *stochastic volatility models* could be considered (Andersen, 2007; Broto & Ruiz, 2004; Taylor, 1994). In these models, volatility is not represented as a constant parameter, but is rather modelled

[36] If 100 observations were used as suggested by Croghan et al. (2017), the estimated standard error would be $\hat{\sigma}_{\mu_D} = 0.270\,\%$ and $\hat{\sigma}_{\sigma_D} \approx 0.192\,\%$. With 1000 observations, the estimated standard error is $\hat{\sigma}_{\mu_D} = 0.085\,\%$ and $\hat{\sigma}_{\sigma_D} \approx 0.060\,\%$.

by means of a stochastic process. As such, *stochastic volatility models* have already been used extensively in the field of financial options valuation. However, to the best of the author's knowledge, there are no documented applications of stochastic volatility models in the context of ASP.

Another point to consider is the distribution of the variable to be modelled. GBM is based on the assumption that ratio $\frac{D_t}{D_0}$ follows a log-normal distribution (Ross et al., 2012). This assumption needs to be verified for the variable to be modelled based on historical observations. However, because only a dataset covering 11 consecutive years is available in this study, this assumption could not be verified. Rather, it was assumed that the distribution of the input data is according to specifications, which is a procedure that has also been applied by other studies on flexible engineering systems (Cardin & Hu, 2016; Cardin, Xie et al., 2017; Hu et al., 2018; Hu et al., 2020). Further, because GBM is based on a log-normal distribution, extremely rare events such as a stock market crash can only be reproduced to a very limited extent. By replacing the log-normal distribution which GBM is based on with a log-Student-t distribution, as proposed by Nkemnole and Abass (2019), rare events could be modelled better.

Finally, another limitation of GBM is that no jumps can be modelled (Mun, 2002). In the context of the application presented in this study, jumps describe instantaneous changes in demand, which can occur at airports due to, e.g. the market entry or the withdrawal of an airline. Especially at airports where LCCs have a large share of the market, such sudden changes in demand can be observed (Chambers, 2007; Jimenez et al., 2017). In order to remedy this deficiency of GBM-based models, it would be feasible to examine the application of so-called *jump diffusion processes*. In this respect, GBM has been extended to allow for abrupt jumps which are often modelled with a Poisson process. While *jump diffusion* is frequently used for the valuation of financial options (Kou, 2002; Merton, 1976) and also for the valuation of real options (Mun, 2002), the literature covers to the author's best knowledge no ASP related applications.

6.1.2 DHL demand model

In order to convert annual aggregated demand scenarios into airport passenger terminal facility-specific DHL demand scenarios, the DHL model presented in Section 4.2 is applied in this study. This DHL model consists of two sub-models: the *unsaturated DHL model* and the *saturated DHL model*. While "the unsaturated DHL model considers the relationship between observed passenger flows in the terminal and aggregated annual demand data, [...] the saturated DHL model includes several operational constraints which limit the actual DHL [of an airport passenger terminal facility], such as limitations in the runway system or the fleet mix operating at an airport" (Waltert et al., 2021, p. 1). Thus it can be seen that the DHL model provides answers to research questions RQ2 and RQ3.

In terms of the DHL demand scenarios generated for *Check-in 1 and 3*, the results presented in Section 5.3.2 are in line with expectations and show annual aggregated demand scenarios can be converted into DHL demand scenarios for airport passenger terminal facilities in an efficient and effective manner. Regarding the results presented in Figure 5.5 on page 154, it is particularly noticeable that the volatility of the generated DHL scenarios seems to depend on the DHL model type. As can be inferred from Figure 5.5, data calculated with the unsaturated DHL model (red lines) shows higher variability than data calculated with the saturated DHL model (black lines). The unsaturated DHL model converts the annual aggregated demand scenarios of an airport directly into a DHL demand scenario of a facility. Thus, DHL demand determined with the unsaturated DHL model shows the same volatility as the annual aggregated demand data. DHL demand determined with the saturated DHL model, however, further depends on the capacity of an airport's runway system as well as on the average number of passengers per aircraft movement, i.e. is dependent on the aircraft types. Both factors have a dampening effect on the volatility of the resulting DHL demand, as they restrict the maximum possible traffic volumes. For this reason, the results of the saturated DHL model are subject to less volatility.

The fact that capacity saturation tends to lead to less DHL demand volatility might positively influence the success of strategic plans for airport passenger terminal facilities. Less volatility means less uncertainty and thus a higher probability that the facility requirements determined will prove to be correct in hindsight. Therefore, even though airports are usually interested in avoiding capacity saturation for economic reasons, this study shows that capacity saturation can lead to positive effects for the strategic planning of airport passenger terminal facilities.

The DHL model is founded on the ratio-based approach, which is an "empirical data-driven method that aims to model the relationship between the DHL [of an airport passenger terminal facility] and annual [aggregated] demand [of an airport] by means of constant ratios or regression models" (Waltert et al., 2021, p. 2). Thus, the DHL model is simple and intuitive, as the method is based solely on the assumption that the relationship between the annual traffic volume and the DHL of a facility can be expressed by means of a ratio. Apart from the availability of a set of measurement data describing both the annual aggregated demand and the facility-specific DHL demand, no further inputs are needed for the unsaturated DHL model. The need for additional input data is also limited for the saturated DHL model, which relies on supplementary data that is either available in the public domain or information which can be provided by an airport's planning department without difficulty.

This study proposes the application of passenger flow data collected with a PTS in order to determine the DHL of an airport passenger terminal facility. To this end, there is a novel approach presented which demonstrates how (big) data that is automatically collected by means of a PTS can be used for planning tasks in the context of ASP. In order to determine DHL demand to a high degree of accuracy, passenger flow data must be recorded as continuously as possible over several years. Collecting data in this way is only possible if the measurement is fully automated, for example by means of a PTS. If such data were generated by means of human measurement, the data collection process would be far too expensive and most probably of substantially lower accuracy.

For the strategic planning application presented in this study, it can be argued that the ratio-based approach suggested is more advantageous for airports than the *design day schedule method*. The ratio-based method allows for a direct conversion of annual aggregated demand into facility-specific DHL demand in only one step, which is both efficient as well as straightforward. The *design day schedule method*, however, is based on two working steps, both of which are labour-intensive. In a first step, fictitious flight schedules for future design days or design weeks are created based on a substantial amount of input data. In order to describe future flight schedules, planners have to make assumptions on future traffic patterns, aircraft types in use, future user groups, etc. Also, specialised software is often used to create design day flight plans. In a second step, design day schedules are converted into airport passenger terminal facility-specific DHLs. This is a complex task, for which airport planners often use discrete-event simulation models, agent-based simulation models, accelerated time simulation models or queueing theory models (Waltert et al., 2021).

Another advantage of the DHL model is its versatility. Due to its generic structure, the DHL model can be applied to various airport passenger terminal facilities. In order to parametrise the DHL model for a different airport passenger terminal facility, airport planners only need a sufficiently large dataset characterising the passenger flow through this facility. Moreover, the DHL model can not only be applied to ZRH Airport, but rather to any airport, regardless of the DHL definition in use at these aerodromes. On this matter, Waltert et al. (2021, p. 9) write that "in this study the SBR has been used to determine the DHL of an airport facility, since this is the method used at ZRH Airport. Without any loss in generality however, the methodology presented in this [document] can also be applied to other DHL definitions, such as the BHR [or the TPHP], which are used at other airports".

Regarding the structure and parametrisation of the proposed DHL model, Waltert et al. (2021) discuss the following topics:

> The unsaturated DHL model is based on a transformation function as [suggested in Equation 4.4 on page 98] which considers the natural logar-

ithm of the annual demand. During intensive testing this type of transformation function was found to be the most optimal in terms of performance. This is most probably due to the fact that with increasing traffic, the growth of the DHL is often less pronounced (De Neufville et al., 2013; Kennon et al., 2013). Large airports might apply certain pricing schemes such as peak-pricing or congestion pricing to control demand, or regional flights may be substituted with rail connections (Berster et al., 2015). Moreover, especially at airports with either high traffic volumes or capacity constraints, the hourly, daily, monthly and seasonal variation in the number of flights, and thereby also the variation in the number of passengers per unit time becomes less pronounced with increasing annual demand. This has a direct impact on the growth of the DHL (Reichmuth et al., 2011; Wilken et al., 2011). Unfortunately, however, the effects reported in the literature cannot be fully confirmed in this study, since no input data originating from international airports with an annual demand of more than 50 million passengers is available. Considering the quality of fit of the unsaturated DHL model, [see Section 5.3.2], the model for ZRH [Airport] is significant at the 5 % level.

The saturated DHL model is based on three components: the hourly departure throughput capacity of an airport, the linear regression model describing the average number of passengers per ATM and the model for ratio r_i. Considering the departure throughput capacity of an airport, it is important to acknowledge that even though the method proposed in this paper assumes the presence of a single value for μ_R, the actual throughput of a runway system is a dynamic property which depends on the runway configuration currently in use, weather conditions, the fleet mix, the share of departures and arrivals, etc. (De Neufville et al., 2013). For this reason, it is advisable to use various different values of μ_R in order to explore the influence of runway capacity on the output of the saturated DHL model. The model for the average number of passengers per ATM is based on data sourced from *Airport Council International* and *Wikipedia*. Based on results presented in [Figure 4.5 on page 101 and Figure 5.4 on page 153], it can be inferred that the relationship between the average number of passengers per movement and annual passengers may approach a certain limit value. This observation is supported by the literature. According to Berster et al. (2015), airlines tend to schedule aircraft with higher seat capacity to airports with high(er) demand and airports which are capacity constrained. Since the variety of aircraft types, especially in the wide-body aircraft market segment is limited, there will be a natural limit of maximum possible number of passengers per ATM. Indeed, Berster et al. (2015) report that in the case of *Emirates Airlines*, which operates almost exclusively large wide-body aircraft, the average number of passengers per ATM is approximately 240.

Additionally, one of the independent variables considered for the average passenger per ATM model is the number of runways available at an airport. This variable has been chosen as a proxy for the maximum throughput of a runway system, since it is readily available in the public domain. Nevertheless, airport planners must handle this variable with care for real-world applications. In reality, airports with multiple runways often only operate some of the available runways simultaneously. Consequently, the proposed model might not fully reflect daily operations. To partially cope with this deficiency, the results presented in [Section 5.3.2, and Figure 5.4 on page 153] are solely based on input data covering airports with 2 or 3 operational runways, since at ZRH Airport and Airport 2 no more than 3 runways are available for use.

[Moreover], the existence of estimated ratios r_i whose value is close to 1 (see [Section 4.2.4]) or even larger than 1 is especially interesting, since one could assume that this should not be possible. In reality the opposite is true, as ratio r_i combines two separate effects in one single constant, namely (i) the

> number of passengers using facility *i* per ATM and (ii) the ratio of design hour passengers per ATM to annual average ATM per ATM. While the first effect can never exceed an aircraft's capacity, it is perfectly legitimate to assume a higher utilization of aircraft during peak periods than the yearly average. Finally, for reasons of simplicity, it has been decided to estimate ratio r_i with the median of the observed data rather than applying a more sophisticated regression model. Given the fact that the DHL models presented in this [study] are applied in the area of airport strategic planning, which is subject to significant uncertainty, such a simplification is justifiable, as long as the planners are aware of the accompanying limitations. (pp. 7–8)

The fact that factor r can be volatile in practical applications is, however, a limitation of the DHL model. Factor r_i depends on $PAXATM_{i,t}^{dh}$ which refers to the average number of passengers per ATM using facility i during the design hour of planning phase t. At small airports, or at airport passenger terminal facilities that are frequented by only a few passengers, e.g. a check-in facility for first class passengers, it is possible that slight changes in the demand structure during the design hour, e.g. one ATM per design hour more or less, can have a large influence on $PAXATM_{i,t}^{dh}$ and thus also on factor r_i. Therefore, practitioners need to be aware that factor r_i can be subject to substantial fluctuation. For precisely this reason, planning experts at FZAG assume that factor r_{CH} can be estimated as $\hat{r}_{CH} = 1$ for the planning example presented in Chapter 5.

Because of its sensitivity to changes in the demand structure, airport planners can use factor r_i to create and investigate *what-if* scenarios. By deliberately changing the value of factor r_i, airport planners can evaluate how the DHL of an airport passenger terminal facility is affected by changes in the demand pattern during the design hour. For instance, planners could therefore evaluate how the market entry of a LCC airline or the termination of operations of a hub carrier influences the DHL of a specific airport passenger terminal facility. In a similar manner, the impact of sudden changes in the fleet mix operated from an airport on the DHL of a facility could be assessed.

6.2 Research area 2 – Facility requirements

At the core of research area 2 are research questions RQ4 and RQ5, which ask whether conventional and flexible CEP models presented in the literature can be adapted in such a way that conventional and flexible facility requirements for airport passenger terminal facilities can be created. The discussion of research area 2 is divided into two parts: Section 6.2.1 focuses on the valuation model, while all the CEP models presented in this study are discussed in Section 6.2.2.

6.2.1 Valuation model

The CEP models presented in this study use the valuation model in order to evaluate facility requirements. According to the literature (De Neufville, 1990; De Neufville & Scholtes, 2011; Martínez-Costa et al., 2014; Van Mieghem, 2003), the valuation model is based on the DCF method, which is referred to by certain scholars as the "workhorse" of infrastructure project evaluation methods (Geltner & De Neufville, 2018, p. 2). Because this method is so widely used in the literature, it can be assumed that its use in this study is appropriate and correct. Nevertheless, in terms of the valuation model as applied in this study, three specific issues require further discussion: (i) the interpretation and definition of the NPV function, (ii) the selection, structure and parametrisation of the cost functions, and (iii) the selection, structure and parametrisation of the revenue functions.

Definition of the NPV function. The NPV of a project or facility is defined as the discounted sum of *all* cash flows accumulating over a period of time, see Section 2.4.1. In contrast, the NPV function applied in this study considers *exclusively* cash flows that arise during the design hours of the planning phases t. All other periods of time, and thus all other cash flows, have been omitted. Therefore, from a purely technical perspective, it is not the NPV of an airport passenger terminal facility that is calculated, but rather the sum of all discounted cash flows that amass during the design hours. Nevertheless, it was decided to use the term *NPV* in this study, because the structure of the NPV formula applied in this document, see Equation 4.10 page 105, is identical with the NPV function presented in the literature (De Neufville, 1990; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018). Furthermore, the restriction of the NPV function to the design hours applied in this work can be justified, since the NPV is used exclusively for the comparison of different facility requirements, but not for the actual financial evaluation of the project in the context of corporate finance, e.g. in determining the net profit or net loss of a project.

Because the NPV function used in this study refers exclusively to the design hours, the resulting ENPVs of optimal facility requirements for *Check-in 1 and 3* presented in Chapter 5 must be interpreted in this context. According to Cardin (2014) and De Neufville and Scholtes (2011), flexible engineering systems have been shown to perform between 10 % and 30 % better in economical terms than comparable conventional systems. Although flexible designs for *Check-in 1 and 3* presented in this study show better performance than their conventional counterparts, the magnitude of the benefits mentioned in the literature are not attained. For instance, in *Evaluation 1*, the ENPV of the flexible facility requirements determined with the CGDRM is only 5.90 % higher than the baseline model result, while the flexible facility requirements determined with the RFDRM show a 5.29 % better performance over the baseline model. Thus, the results presented in this study are significantly lower than the values published in the literature. An explanation for this can be found in the definition of NPV which is used in this work. During the design hour, airport passenger terminal facilities experience "peak traffic but not … absolute maximum traffic" (De Neufville et al., 2013, p. 539). The facilities are therefore well utilised, which often leads to increased levels of congestion and delay. Revenues and costs are determined exclusively for these operating conditions in order to estimate the NPV of the airport passenger terminal facility. The revenue function implemented in this study depends linearly on DHL demand. Thus, increased demand levels automatically lead to increased revenue. As for costs, however, congestion-related penalty costs are expected to be disproportionally higher during the design hours compared with an average operating hour, since the relationship between the utilisation of an airport passenger terminal facility and the resulting level of congestion is to a great extent non-linear, see Section 2.4.2. Thus, the difference between revenues and costs, which determines the NPV of an engineering system to a large extent, is smaller during the design hour than during an average operating hour. This may explain why the benefits of flexible facility requirements obtained in this study are lower than the values mentioned in the literature.

Cost functions. The proposed valuation model considers installation, operational and penalty cost functions. The functions applied to model installation and operational costs are commonly used in the literature. Of particular note is the way in which (i) installation costs for changes in building space requirements and (ii) penalty costs are estimated. As reviewed in Section 2.1.3, the literature presents several methods to determine the space requirements $\Delta A_{i,t}$ given a capacity adjustment of $\Delta K_{i,t}$. The calculation approach proposed in this study is based on the rule-of-thumb model presented in IATA (2017), and is capable of estimating the required building space through a series of simple calculations and assumptions. Nevertheless, this type of calculation is not as accurate as a DES model or an agent-based model (Wu & Mengersen, 2013). However, the accuracy of the model is of little importance in the proposed application, since all the advantages in terms of precision offered by complex models are usually outweighed by the high levels of uncertainty ASP is subject to. Furthermore, complex models are computationally expensive and often require proprietary software; both of these difficulties can be circumvented with the rule-of-thumb model applied in this study.

In order to monetise the negative effects of congestion and delays on the perceived service quality, so-called penalty costs are established. In the literature, two different approaches to calculate congestion-related costs are mentioned. The first approach monetises congestion by multiplying the expected waiting times experienced by passengers with the *value of time*, which quantifies the monetary value of an hour's wait for a single passenger. Although certain authors, such as Sun and Schonfeld (2015) and Yoon and Jeong (2015), use this approach to quantify delay-related costs, it is ultimately questionable whether the passenger's wait of some period of time can be quantified in terms of money, since passengers experience waiting times differently (Durrande-Moreau & Usunier, 1999; Van Hagen, 2011). Moreover, it can also be argued that the costs of passengers' waiting time should not be considered in the calculation of the NPV of an airport passenger terminal facility, since these costs refer to the users, but not to the actual infrastructure.

The second approach proposed by the literature is based on charging penalty costs when too much or not enough capacity is provided. This approach, originally proposed by Saffarzadeh and Braaksma (2000) for an application in the context of operational airport planning, is used in this study. The advantage of this method is that delay-related costs can be directly linked to the operational infrastructure that is available at a certain facility. In contrast to monetised waiting times, it can be argued that such costs may be included in the NPV calculation as they relate to the capacity of an airport passenger terminal facility. The parametrisation of the penalty cost function is most probably the weak point of the proposed method. There is no reference in the literature to the parameter values for the penalty cost function, but there must rather be determined by the planners in a *trial-and-error* process. This process, which requires "engineering judgement" (Saffarzadeh & Braaksma, 2000, p. 77), leaves room for ambiguity and errors. However, the sensitivity analysis conducted in Section 5.4.1 showed that the results of the CEP models presented in this study are only dependent to a small degree on the parametrisation of the penalty cost function. Thus, it can be assumed that any inaccuracies in the parametrisation of the penalty cost function have only a marginal effect on the results of the CEP models[37].

Revenue functions. In this study, revenues generated by airport passenger terminal facilities are attributed to three different sources: revenues from airport charges and taxes

[37] Saffarzadeh and Braaksma (2000) come to a similar conclusion. As such, Saffarzadeh and Braaksma explain that it is not the absolute values of the parameters of the penalty cost functions which affect the results, but rather the relative relationship between the parameters.

paid by passengers, revenues from user charges paid by handling agents and airlines, and revenues originating from the provision of food, beverage and retail services. In all three cases, the estimation of revenues is based on linear functions. Although this approach is simplistic, it corresponds exactly to the methods documented in the literature, see Section 2.4.2. Revenues generated by the provision of retail, food and beverage services deserve special attention. The retail revenue function used in this study assumes that revenues are solely dependent on the size of the building space allocated for retail purposes. While this model structure does facilitate a first approximation of the retail revenues, many important factors that significantly influence retail revenues are neglected. There is, therefore, scope for improved retail revenue models to be applied taking into account additional factors, such as the location where the services are provided, the actual types of services offered, demographic factors, time of the year, etc. (Chen et al., 2020; Davis et al., 2018; Volkova, 2009).

6.2.2 CEP models

In this study, four different CEP models were developed and presented; these are used to determine which stochastically optimal conventional and flexible facility requirements for airport passenger terminal facilities. For this purpose, both conventional and flexible CEP models mentioned in the literature were adapted so that they can be applied in an ASP-related context. In the following section, all four CEP models presented in this study are discussed individually.

Baseline model. The baseline model is formed on the assumption that the capacity of a facility is adjusted by $\Delta K_{i,0}$ units at time $t = 0$ only. After this initial adjustment, the capacity of a facility can no longer be changed. It is clear that this assumption is far from realistic, as no practitioner would ever plan a facility under these principles. However, the baseline model was not designed to create realistic facility requirements, but rather the results are used exclusively to determine the VoF of facility requirements created with the fixed model, the CGDRM and the RFDRM.

The baseline model consists of one single decision variable, $\Delta K_{i,0}$, whose feasible values are extensively limited. For this reason, the solution space of the baseline model is comparatively small, and thus the application of an enumeration-based solution procedure is computationally viable. It could well be questioned whether a better performing solution procedure might be applied, i.e. one which generates optimal solutions in less computing time and/or one which does not need to evaluate each solution candidate on an individual basis. However, it is questionable whether the extra effort required to determine a more efficient solution procedure is worthwhile, as the baseline model is exclusively used for benchmarking purposes and not for the evaluation of large numbers of different candidate flexibilities. Consequently, it might make more sense to design more efficient solution procedures for CEP models, by means of which a large number of different system designs can be investigated, or for CEP models that have large solution spaces. It is because of this problem of large solution spaces that evolutionary algorithms are used for the fixed model, the CGDRM and the RFDRM.

Fixed model. The fixed model is based on the adaptation of conventional CEP models presented in the literature (Freidenfelds, 1981; Geng & Jiang, 2009; Julka et al., 2007; Luss, 1982; Martínez-Costa et al., 2014; Van Mieghem, 2003; Wu et al., 2005). The solution of the fixed model is a stochastically optimal capacity vector $\mathbf{K}_i^*$ which specifies the optimal capacity of a facility i in all planning phases t. The results of the fixed model are thus easy to understand and comprehend for practitioners, since capacity vectors describe precisely when and how a certain infrastructure is to be adjusted.

From a practitioner's perspective, the proposed GA-based solution procedure is particularly noteworthy. Because GAs are especially well suited for the determination of near-optimal solutions of complex, non-linear and heavily constrained optimization problems (Bäck, 1996; Fogel, 2006; Holland, 1992; Michalewicz, 2013), the author believes that GAs are particularly appropriate for an application in the context of the fixed model.

GAs allow the formulation and definition of objective functions, constraints and inputs in a flexible manner. For example, the objective function of the fixed model does not need to be linearised or approximated[38]. This enables airport planners to tackle practical problems without having to develop complex models and solution methods or to make highly simplifying assumptions. Furthermore, various open-source software implementations for GA solvers are available, such as the *DEAP* software library for the *Python* programming language used in this study, thus avoiding the use of (expensive) proprietary software. Finally, the basic principles of evolutionary optimization algorithms are straightforward and can be explained to the interested layman without further ado. This can be rather useful for practical applications in the context of ASP, since decision makers might prefer solutions and methods that are simple, clear and comprehensible from their point of view.

As shown in Figure 5.21 on page 192, the fixed model comes with a faster solution time than the CGDRM and the RFDRM. Moreover, the results suggest that the fixed model converges to a stable near-optimal solution within approximately 100 generations. Both facts are clear indications that the solution procedure proposed for the fixed model is efficient and effective. As is the case for all GA-based solution procedures, however, no reliable statements can be made about the accuracy of the determined near-optional solution(s). If such accuracy specifications were needed, approximate algorithms could be used as an alternative solution procedure, see Section 2.4.3.4. However, it is questionable whether such highly accurate solutions are even needed at all for the application proposed in this study. ASP is characterised by a high degree of uncertainty and long planning horizons, which means that the solutions identified, i.e. the optimal facility requirements, do not have to be highly precise, but only *good enough* given the circumstances.

Conditional-go decision rule model. The CGDRM is based on the *empirical approach*, in which planners define the structure of a decision rule based on a priori knowledge and

[38] Please note that CEP models for ASP purposes presented in the literature routinely apply linearisations and approximations. For instance, linearisations are proposed by Sun and Schonfeld (2015, 2016, 2017), while Solak (2007) and Solak et al. (2009) apply approximations.

practical experience. The stochastically optimal parametrisation of the decision rule is subsequently determined by means of an appropriate solution procedure. For the CGDRM presented in this study, a conditional-go decision rule, which is based on a logical *if-then-else* operator, was selected for a number of reasons. First, conditional-go decision rules have often been used in the literature on flexible engineering systems and are therefore already well established in the scientific community. In fact, the CGDRM presented in this study is based on the basic structure of flexible CEP models presented in the works of Cardin and Hu (2016), Cardin et al. (2015) and Hu et al. (2018). Secondly, conditional-go decision rules are easy to understand; this facilitates their acceptance by decision makers for practical applications. Finally, conditional-go decision rules are simple to apply, as DMs only need to follow the decision rule in each planning phase and act according to the outcomes of the rule.

The conditional-go decision rule used in this study is quite simplistic, only taking into account DHL demand $d^s_{i,t}$ in planning period t and the operational capacity $K^s_{i,t-1}$ of facility i that is available at the beginning of the planning period t of scenario s. Therefore, there is great potential to extend and potentially improve the applied conditional-go decision rule with a number of measures. First, the rule could consider not only information referring to planning period t, but several planning phases $t, t-1, t-2, \ldots$[39]. Also, additional factors, such as installation and operational costs, revenues, the temporal and spatial target LoS, as well as the observed LoS, could be considered in a conditional-go decision rule. Moreover, it would also be interesting to consider dependencies between different passenger terminal facilities, e.g. the knock-on effect of delays in a passenger terminal.

Despite the rather limited solution space of the CGDRM, a GA is used for the solution procedure. One reason for choosing a GA to solve the CGDRM in this study was to benefit from synergies with the solution procedure proposed for the fixed model. Further, a GA allows the conditional-go decision rule, i.e. the *if-then-else* operator, to be directly

[39]This approach has been applied for example by Cardin, Xie et al. (2017).

integrated into the objective function by means of software that is implemented during the solution process. Moreover, the fact that the conditional-go decision rule is expressed in software provides planners with the opportunity to adapt, modify and change the rule on a flexible basis. Finally, in comparison with other solution approaches for conditional-go decision rule-based CEP models mentioned in the literature, a GA-based approach is much simpler and more straightforward than other solution procedures documented in the literature. For example, Zhao et al. (2018) present a multi-facility CEP based on a multi-stage stochastic model, in which a conditional-go decision rule is integrated by means of the constraints the optimisation problem is subject to. Using such an approach results in a significantly more complex model structure and solution procedure.

Reward function decision rule model. The RFDRM is a flexible CEP model based on the *generative approach* in which the optimal structure of a decision rule as well as its optimal parametrisation are determined. Thus, the RFDRM is undoubtedly the most complex of all CEP models for airport passenger terminal facilities presented in this study. This is manifest in the fact that a very specific solver, namely the GEP algorithm, is used to determine stochastically optimal flexible facility requirements for the RFDRM.

Theoretically, the *generative approach* comes with one big advantage over the *empirical approach*; because both the optimal structure and the parametrisation of a decision rule are determined during the solution procedure, globally optimal flexible facility requirements can be determined. This is not possible with a CEP model based on the *empirical approach*, since the structure of the decision rule is determined in advance. Thus, it is possible that with the chosen structure of an *empirical approach*-based decision rule the global optimum can never be reached.

Although the *generative approach* addresses the shortcomings of the *empirical approach* mentioned above, the RFDRM does have certain limitations. In the literature (Hu et al., 2020; Hu & Guo, 2019) as well as in this study, flexible CEP models based on the *generative approach* are solved with the GEP algorithm in which computer programs encoded in fixed-length chromosomes are evolved over a number of generations. The use of the GEP algorithm brings to light limitations because, on the one hand, the chromosomes have a fixed length and, on the other hand, the genes of the chromosomes can only take on values that are specified in predefined sets. In the GEP algorithm, an individual chromosome is decoded into exactly one computer program, i.e. a decision rule, using the *width-first search scheme* method. This means that longer chromosomes have the potential to represent more complex computer programmes than shorter chromosomes. Since the length of chromosomes is fixed, it can be inferred that the complexity of the computer programs which can be represented with GEP is also limited. In addition, the genes of the chromosomes may only take on values that are defined in the appropriate sets of *terminals* Γ and *functions* Ψ. This leads to a further restriction of the number of potentially possible chromosomes and therefore also the number of encodable computer programs (Ferreira, 2001, 2006; Zhong et al., 2017). It could be proposed to increase the length of the chromosomes as well as the number of elements in the sets Ψ and Γ in order to encode both a larger number and more complex computer programmes. In both cases, however, this would involve an extension of the solution space, which could negatively affect the solution time of the GEP algorithm. Moreover, neither of these measures actually solve the problem, as the number of possible chromosomes remains limited.

Another limitation of the GEP algorithm is that the solution procedure is based on a priori knowledge, since the elements in the sets Ψ and Γ have to be defined by practitioners based on empirical knowledge. This limitation cannot be bypassed, since GEP is based on the fact that both sets are known and defined. However, possible extensions of the two sets could be considered. The set of *functions* Ψ already contains all basic operators[40] and is therefore difficult to extend. However, the set of *terminals* Γ applied in this study would most probably be suitable for extensions. For the application proposed in this study, Γ consists of the features V_l of adjustment options $e_l \in e$. Additional features, such as target and observed LoS, operational costs, delay-related costs or revenues could

[40]The set of functions Ψ includes the addition, subtraction, multiplication and protected division operators

be considered. Whatever additional elements might be proposed, practitioners must take into account that each additional element in sets Ψ and Γ increases the solution space of the RFDRM, a fact which might negatively affect the required solution time.

The evaluation of a population of chromosomes with the RFDRM takes about 10 times longer than with the fixed model or the CGDRM, see Figure 5.21 on page 192. This shows, together with the fact that the RFDRM reaches a stable solution after about 50 generations, while the CGDRM is stable after 20 generations, that the solution procedure of the RFDRM is comparatively inefficient.

Regarding the optimal reward functions generated by the RFDRM in general, the results presented in this study neatly demonstrate that reward functions are comprehensible and their application in ASP is quite straightforward. Indeed, the optimal reward functions generated in this work are simple mathematical terms which are easily comprehensible for laypersons. In comparison to conditional-go decision rules, however, it is noticeable that reward functions are much more difficult to handle for practitioners. In other words, there is no intuitive feeling of what a reward function actually means. Someone who has no detailed knowledge of the GEP algorithm and therefore does not know how stochastically optimal reward functions are determined, could therefore imagine that these decision rules are randomly generated. In practice, this could lead to decision makers not trusting the results of the RFDRM, even if the rules have been generated according to specifications. This could mean that DMs and owners would not apply reward functions in practice.

6.3 Research area 3 – Planning example ZRH Airport

Research area 3 centres on the practical application of the strategic capacity planning framework presented in this study. For this purpose, the aggregated demand model, the DHL demand model as well as the conventional and flexible CEP models are used in a planning example to determine facility requirements for *Check-in 1 and 3* at ZRH Airport. Research area 3 also focuses on answering research question RQ6, which deals with the advantages of flexible facility requirements for *Check-in 1 and 3* in comparison with conventional facility requirements, as well as RQ7 and RQ8, which address the sensitivity of the presented CEP models. Therefore, this section is divided into two parts: Section 6.3.1 discusses the comparison of conventional and flexible facility requirements for *Check-in 1 and 3*, while Section 6.3.2 focuses on the sensitivity of the CEP models.

6.3.1 Comparison of conventional and flexible facility requirements

In this study, the fixed model, CGDRM and RFDRM are used to determine conventional and flexible facility requirements for *Check-in 1 and 3* at ZRH Airport. These models require a number of inputs and parameters, which must be provided by airport planners. Unfortunately, however, various parameters, such as the share of airport charges allocated to the check-in facility or the exact number of check-in desks used during the design hour in planning phase $t = 0$, are either unknown to the planning experts of FZAG or cannot be measured precisely, but rather have to be estimated with engineering judgement or assessed based on operational experience. This reveals an important limitation of all CEP models; the more precise and detailed the models are, the more inputs and parameters have to be specified, which, however, cannot always be achieved at the desired level of accuracy. Practitioners must therefore be aware that the results obtained with the CEP models presented in this study are not highly accurate, but are simply approximations. In awareness of this general limitation of the CEP models presented here, *Evaluation 1, 2 and 3* will be discussed separately below.

6.3.1.1 Evaluation 1 – Option to defer & option to alter scale

Evaluation 1 considers the *option to defer* and the *option to alter the scale* of the future development of *Check-in 1 and 3* at ZRH Airport. As such, these real options *on* systems are understood as the basic building blocks of flexibility which *Evaluation 2* and *Evaluation 3* are based on. The results clearly show that flexible facility requirements for *Check-in 1 and 3* perform better than conventional facility requirements in

Evaluation 1. This is explained by the following. First, the resulting ENPV and VoF of flexible facility requirements are significantly[41] higher than the corresponding results of conventional facility requirements: the CGDRM and the RFDRM lead to facility requirements which result in an ENPV which is 5.90 % and 5.29 % higher than the ENPV of facility requirements determined with the baseline model. In comparison, conventional facility requirements determined with the fixed model perform only 1.79 % better than the baseline model. However, as discussed in Section 6.2.1, the major drawback is that flexible facility requirements for *Check-in 1 and 3* perform less well than comparable engineering systems mentioned in the literature[42]. Secondly, the target curves of flexible facility requirements for *Evaluation 1*, see Figure 5.8 on page 163, are to the right of the target curves for conventional facility requirements. This indicates that, in general, flexible facility requirements are economically more valuable than conventional facility requirements. It is particularly striking that the difference between the VaR of flexible facility requirements and the VaR of the baseline model is greater than the difference in VaG between the models. One reason for this could be that the *option to defer* and the *option to alter the scale*, which are both examined in *Evaluation 1*, are especially advantageous in poor market conditions. This finding, which is also supported by the literature (Cardin & Hu, 2016; Hu et al., 2016; Zhao et al., 2018), is plausible, since the *options to defer and to alter the scale* provide decision makers with the opportunity to wait for better market conditions, which is particularly valuable when a system has not yet been built. Once a system is built, however, only the option to alter the scale provides airport planners the flexibility to make adjustments. Yet, this flexibility is seriously limited by the irreversibility of investments in capacity.

A comparison of flexible facility requirements created with the CGDRM and the RFDRM for *Evaluation 1* shows that both models lead to almost identical VaR. Both models can thus cope similarly well with unfavourable market conditions. In a good market envir-

[41]The results of the CEP models for *Evaluation 1* are significantly different, as has been demonstrated with *standard two-sided z-test for mean*.

[42]The literature indicates that flexible engineering systems present between 10 % and 30 % better economic performance (Cardin, 2014; De Neufville & Scholtes, 2011; Nembhard & Aktan, 2009).

onment, however, the application of conditional-go decision rules leads to a higher VaG than flexible facility requirements based on reward functions. It would be interesting to compare these findings with the literature. Unfortunately, however, neither Hu and Guo (2019) nor Hu et al. (2020), which are the only contributions in the literature where reward function models are applied, compare the results of reward function-based facility requirements with conditional-go decision rule-based requirements at the desired level of detail.

6.3.1.2 Evaluation 2 – Modularisation

Evaluation 2 extends *Evaluation 1* by additionally considering modular future development of *Check-in 1 and 3*. The modular development of airport terminals and facilities is one of the ways in which flexibilities can be introduced in these systems (Kincaid et al., 2012; Shuchi et al., 2012; Shuchi, 2016). Modularisation allows buildings and facilities to be expanded easily, as the interfaces between individual modules are clearly defined.

With regard to the results of *Evaluation 2*, it is noticeable that the choice of large(r) module sizes for *Check-in 1 and 3* is especially beneficial for conventional facility requirements. In contrast, flexible facility requirements do not seem to benefit from large modules. For conventional facility requirements determined with the fixed model, modularisation leads to a significant improvement of the system's ENPV of 405 CHF compared with the optimal solution determined in *Evaluation 1*. For flexible facility requirements, however, modularisation improves the ENPV of *Check-in 1 and 3* only marginally by 8 CHF for the CGDRM and 11 CHF for the RFDRM, respectively.

With regard to the optimal module size, the results of this study clearly show that practitioners cannot plan according to the principle of *the bigger, the better*, but they rather have to determine the optimal module size e_m^* on a case by case basis. In general, the results suggest that module sizes which are too large significantly reduce the ENPV and VoF of facility requirements for *Check-in 1 and 3*. One explanation for this could be that larger modules limit the flexibility of planning, since the capacity of the system can then only be changed in large, but not small steps. Maintaining this planning flexibility seems to be particularly important for flexible facility requirements, which can be illustrated especially well by the target curves in Figure 5.13 on page 175. For flexible facility requirements, the target curves for a module size of $e_m = 1$ are, in almost all cases, to the right of the target curves for $e_m > 1$. This is an indication that large(r) module sizes are only advantageous in very rare cases for flexible facility requirements. This finding coincides with Miller and Clarke (2010, p. 72), who conclude that "[flexible] strategies with small … capacity increase are likely to have a higher expected NPV"[43]. For conventional facility requirements determined with the fixed model, however, target curves for $e_m > 1$ and e_m for which the resulting ENPV is greater than or equal to $0.98 \cdot ENPV^{max}$ are to the right of the target curve for $e_m = 1$. Thus, modularisation tends to be beneficial for conventional facility requirements as long as the module size is selected appropriately.

The results of this study indicate that planners must clearly distinguish between the benefits of modularisation from a planning and architectural perspective (common interfaces, expandability, etc.) and benefits in terms of the financial value of modules (ENPV, VoF). Modules allow airport terminals and facilities to be expanded and adapted easily. They are therefore of great importance for the planning and design of buildings and facilities. With regard to the financial value of facility requirements, however, practitioners must be aware that modularisation is not simply a *carte blanche* for highly valuable facilities. For conventional facility requirements, the optimal module size must be chosen carefully and flexible facility requirements seem to benefit from module sizes $e_m > 1$ only in very specific circumstances. This finding is highly relevant for (the) practical application, as the use of modularisation is mentioned in the literature as a means of introducing flexibility in ASP (Kincaid et al., 2012).

[43] Miller and Clarke (2010) examine investments in air transportation in general.

6.3.1.3 Evaluation 3 – Buffer space

Evaluation 3 extends *Evaluation 1* with the ability to determine optimal facility requirements for *Check-in 1 and 3* that take buffer space into account. For the discussion of the results, a clear distinction is made between applications in which buffer space remains unused until it is converted into a facility versus buffer space which is temporarily used for the provision of retail services.

Buffer space without retail utilisation. Buffer space which is not used for retail purposes gives planners the flexibility to expand an airport passenger terminal facility at a later date without having to create new building space. This capability can be very attractive from a planning perspective, as it allows practitioners to respond effectively and efficiently to relatively short-term fluctuations in demand. From a financial perspective, however, the results presented in this study show that the planning of buffer space without retail utilisation has only a limited benefit. In principle, the creation of buffer space without retail utilisation is the exact opposite of a deferral of an investment. Although EoS savings can certainly be made by initially creating larger building spaces, an early investment in buffer space is also associated with opportunity costs: the investment in buffer space ultimately binds capital that could be used elsewhere. This effect is intensified by the fact that (high) premiums are incurred for buffer space, as it must be ensured that a future facility can be connected to or integrated with other facilities at a later date. For example, in case of *Check-in 1 and 3*, buffer space must be designed in such a way that it can be connected to the BHS at any future point in time. These cost premiums are a potential explanation for the observation that the ENPV of *Check-in 1 and 3* planned with buffer space without retail utilisation is lower for all tested CEP models than comparable values achieved in *Evaluation 1* [44]. Nevertheless, the results presented in this study show that the creation of buffer space without retail utilisation can still make sense in certain

[44] Despite the inferior performance compared to *Evaluation 1*, it must be mentioned here that for *Evaluation 3* flexible facility requirements lead to significantly higher ENPV and VoF values than conventional facility requirements generated with the fixed model.

situations. It can be inferred from Figure 5.19 that the inclusion of relatively small buffer spaces without retail utilisation in *Check-in 1 and 3* is worthwhile for flexible facility requirements generated with the CGDRM if market conditions are characterised by high demand growth, i.e. a high percentage drift rate μ_D. Practitioners must therefore carefully examine whether the application of buffer spaces without retail purpose is meaningful for a certain application or not.

Buffer space with retail utilisation. The situation is different for buffer space with retail purpose. For Figure 5.19 it can be inferred that as the size of the buffer space increases, the ENPV of conventional and flexible facility requirements for *Check-in 1 and 3* increases as well. Further, the results clearly show that creating small buffer spaces with retail utilisation is not worthwhile, rather planners should opt for larger buffer spaces. One explanation for this is probably the fact that small buffer spaces have to be converted into a facility relatively quickly and therefore the space cannot be utilised for the more lucrative interim retail usage for a sufficiently long time. However, practitioners must be aware that the results presented in this study can be misleading to a certain degree. it could be inferred that it is advantageous to create the largest possible buffer space with retail use. This, however, is not correct, since the size of the buffer space should be chosen so that at the end of the planning horizon of the ASP project the entire space is utilised. Given the cost premiums, it is certainly not advisable to plan large retail areas, i.e. *shopping centres*, by the creation of buffer space with retail utilisation. Instead, for the construction of retail outlets, planners should plan with *normal* building space.

The results further indicate that the fixed model, the CGDRM and the RFDRM result in negative VoF for almost all buffer sizes tested. In other words, when planning with buffer spaces to be used for retail, the baseline model generates the best results in terms of ENPV. This is, however, not an advantage, but rather a limitation of the baseline model. The baseline model is founded on the assumption that the capacity of an airport passenger terminal facility can only be adjusted at time $t = 0$, while no adjustments may be made in any subsequent planning phases. Consequently, the buffer space made available at time $t = 0$ would never be converted into a complete airport passenger terminal facility. Thus, the buffer space generates retail revenue over the entire planning horizon of the ASP project, which has a positive effect on the ENPV and also explains the low VoF of the facility requirements of the other CEP models.

6.3.2 Sensitivity of optimal facility requirements

The parameters which the results of the CEP models are sensitive to were identified with the help of a tornado diagram, see Figure 5.6 on page 157 (and Figures B.1 and B.2 in Appendix B). In the course of the sensitivity analysis performed for this study, the discount rate δ, the EoS parameters α_K and α_A, the percentage drift rate of demand μ_D, the volatility of demand σ_D and the average service rate $\mu_{K,CH}$ were selected for further analysis. With the exception of the average service rate $\mu_{K,CH}$, the same parameters were identified in this study as in comparable works mentioned in the literature (Cardin, Bourani et al., 2013; Cardin & Hu, 2016; Cardin et al., 2015; Cardin, Zhang et al., 2017; Hu & Cardin, 2015; Hu et al., 2020; Zhang & Cardin, 2017).

Besides the above-mentioned parameters, the results of the CEP models are also sensitive to changes in the parameters of the revenue function. In this study, however, it was decided not to investigate the influence of the revenue function parameters on facility requirements for *Check-in 1 and 3* in more detail. The reason for this is that the parametrisation of the revenue function is not affected by extrinsic factors, but rather controlled exclusively by an airport operator, i.e. FZAG in the presented planning example. Indeed, the parameters referring to passenger and user charges are determined exclusively by FZAG by means of the *airport charges regulation* document (FZAG, 2021).

The remainder of this section discusses the sensitivity of *Evaluation 1, 2 and 3* to changes and variations in the discount rate δ, the EoS parameters α_K and α_A, the percentage drift rate of demand μ_D, the volatility of demand σ_D and the average service rate $\mu_{K,CH}$.

Discount rate. The ENPV of *Check-in 1 and 3* is negatively affected by an increasing discount rate δ in *Evaluations 1, 2 and 3.* This finding is in line with results of other studies presented in the literature on flexible engineering systems (Cardin, Bourani et al., 2013; Cardin & Hu, 2016; Cardin, Zhang et al., 2017; Hu & Cardin, 2015; Zhang & Cardin, 2017) as well as the theory (De Neufville, 1990; De Neufville & Scholtes, 2011; Geltner & De Neufville, 2018; Trigeorgis, 1996).

In the context of ASP, the applicable discount rate value is often predefined by an overriding authority. For instance, FZAG is required by the *Swiss Federal Office of Civil Aviation* to apply a discount rate of between 3.5 % and 4 %, see S&P Global Ratings (S&P, 2019) and Appendix A. Consequently, practitioners usually have little influence on the discount rate and have to work with the *status quo*. One consequence of low discount rates can be that certain real options are less valuable. For example, the value of the *option to defer* an investment in capacity, which is used in *Evaluations 1, 2 and 3*, is especially advantageous at high discount rates, as high discount rates favour a delay of investments (Cardin & Hu, 2016).

EoS parameter. An increase of the EoS parameter values, which is associated with a decrease in the magnitude of the experienced EoS savings, has a negative impact on the ENPV and a positive effect on the VoF of optimal facility requirements for *Check-in 1 and 3* in all *Evaluations* conducted in this study. This is in line with the findings of Cardin and Hu (2016), Cardin et al. (2015) and Hu and Cardin (2015).

If the EoS parameters α_K and α_A have a high value, then fewer or even no cost savings can be made with large capacity adjustments. This leads to the fact that the average installation cost of capacity adjustments tends to be higher with increasing EoS parameter values, which explains the above-mentioned observed reduction of the ENPV for both flexible as well as conventional facility requirements. Therefore, as originally reported by Manne (1961), decision makers are best advised to opt for small capacity adjustments in conditions where no or only small EoS savings can be made. This effect can be clearly illustrated by the example of conventional facility requirements for *Evaluation 2*: with increasing EoS parameter values, the optimal module size e_m^* for facility requirements created with the fixed model decreases, as can be inferred from Figure 5.13 on page 175.

The VoF of optimal facility requirements for *Check-in 1 and 3* increases with increasing EoS parameter values. The reason for this can be found in the baseline model, which only allows for a single, usually very large capacity adjustment at time $t = 0$. Consequently, with increasing EoS parameter values, the ENPV of facility requirements generated with the baseline model decreases, which in turn manifests itself in an increase of the VoF of the facility requirements determined with the other CEP models.

Percentage drift rate of demand. The results of this study indicate that an increasing drift rate of demand μ_D leads to higher ENPV and VoF for all candidate flexibilities except for buffer spaces with retail utilisation, where the opposite applies. The higher ENPV of the facility requirements can be explained thus; a higher percentage drift rate leads on average to a higher DHL demand of an airport passenger terminal facility, which ultimately has a positive effect on passenger-related revenues and thus also on the ENPV. The observed increase in VoF depends on the performance of the baseline model. A higher drift rate leads to either a larger capacity adjustment $\Delta K_{i,0}$ at time $t = 0$ or, if planners choose not to provide more capacity, to an increased probability of under-designed capacity towards the end of the planning horizon of an ASP project. Both cases lead to higher costs, which have a negative effect on the ENPV of facility requirements created with the baseline model and thus a positive impact on the VoF of the other models.

Further, this study clearly demonstrates that flexible engineering systems are better able to cope with percentage drift rate variations on the entire tested range of μ_D, since flexible facility requirements result in consistently higher ENPV and VoF values than facility requirements created with the fixed model. All these findings are consistent with the literature (Cardin et al., 2015; Cardin, Zhang et al., 2017; Hu et al., 2020; Zhang & Cardin, 2017).

For facilities equipped with buffer space with retail utilisation, a higher percentage drift rate leads to a lower ENPV and VoF. Higher demand growth increases the likelihood that a buffer space will have to be converted into a passenger terminal facility more quickly. Consequently, the buffer spaces can be used for less time to generate lucrative retail revenues, which explains the negative impact on an increase in μ_D on ENPV and VoF.

Percentage volatility of demand. An increasing volatility of demand σ_D causes future demand to be subject to higher levels of uncertainty, which, as the results of this study indicate, have a negative impact on the ENPV of facility requirements for *Check-in 1 and 3*. To explain the decreasing ENPV with higher demand uncertainty, a distinction must be made between conventional and flexible facility requirements. With conventional facility requirements, a higher demand uncertainty leads to a greater probability of the provision of sub-optimal capacity, which, due to the characteristics of conventional facility requirements, can no longer be changed. This leads to higher penalty costs and therefore a declining ENPV. In contrast, flexible facility requirements for *Check-in 1 and 3* can cope well with changes in (unexpected) demand growth, as the candidate flexibilities examined in this study have their strengths in this respect (deferral, expansions, etc.). However, if demand decreases, only a limited number of mitigating measures can be taken due to the irreversibility of investments in capacity. Consequently, large-scale over-capacity is created in the event of an unexpected decline in demand, which in turn leads to high penalty costs. This may explain why the ENPV of flexible facility requirements declines when demand uncertainty is high.

Of particular note is the way in which the VoF of facility requirements is influenced by increasing percentage volatility. For all candidate flexibilities examined except for buffer spaces with retail utilisation, it can be seen that the VoF of flexible facility requirements is positively influenced by increasing percentage volatility, while the opposite applies for conventional facility requirements. The results of this study are thus in line with the findings presented in the literature (Cardin, Bourani et al., 2013; Cardin et al., 2015; Cardin, Zhang et al., 2017; Hu & Cardin, 2015; Hu et al., 2020; Xiao et al., 2017; Zhang & Cardin, 2017). Indeed, the increasing VoF of flexible facility requirements as a result of an increase in demand volatility shows very clearly that, as explained by Amram and Kulatilaka (1998) and De Neufville (2003), real options have more value when the levels of uncertainty are high.

The results of this study indicate that if *Check-in 1 and 3* is equipped with buffer space in which temporary retail services are offered, the VoF of the system decreases with increasing demand volatility. This raises the question of whether real options do not function "as intended" in this situation? The reason for decreasing VoF with increasing volatility is not a potential failure of the real options, but rather the influence of the retail revenues, which affect the ENPV of *Check-in 1 and 3* significantly, especially if the buffer space is expansive. Because retail revenues are modelled exclusively as a function of DHL demand in this study, the revenues and therefore the ENPV of *Check-in 1 and 3* are strongly influenced by the volatility of demand σ_D. Therefore, airport planners must be aware that in market conditions which are subject to large demand uncertainty the installation of large buffer spaces that allow for temporary retail usage is associated with risks that can only be mitigated to a limited extent by flexible planning.

Average service rate. The results presented in this study suggest that the ENPV of *Check-in 1 and 3* is negatively affected by an increase of the average service rate $\mu_{K,CH}$ of a check-in desk. This finding is somewhat counter-intuitive, as it would probably be inferred that with an increasing average higher service rate of check-in desks and thus higher productivity of the facility, the capacity required to handle a given DHL demand at a predefined target LoS would decrease. This would result in lower installation and operation costs, which would have a positive impact on the ENPV. Results suggest, however, that cost savings realised by increased levels of productivity of the check-in facility are most probably cancelled out by lost revenues and higher penalty costs. Because fewer check-in desks are needed to meet target LoS at higher service rates, the revenue generated by fees paid by handling agents and airlines decreases with increased service rates. Further, it is possible that at very high service rates the initially installed operational capacity of *Check-in 1 and 3*, i.e. the capacity of the facility identified in the inventory, is found to be over-designed. Thus, (high) penalty costs may be incurred from the planning phase $t = 0$. This effect is clearly illustrated in Figure 5.11 on page 168: above a certain service rate value, the ENPV of *Check-in 1 and 3* decreases markedly. Therefore, the impact of a changing service rate on a system's ENPV is rather complex and multi-faceted, which probably also explains the fluctuations in the dependency between ENPV and the service rate observed in *Evaluations 2 and 3*.

6.4 Implications

This study has a number of implications for ASP in general as well as for facility requirements for airport passenger terminal facilities and candidate flexibilities in the context of ASP in particular.

Implications for ASP in general. The strategic capacity planning framework presented in this study is a tool that can be used directly by practitioners for real-world planning applications in the context of ASP. In the past, airport planners routinely created facility requirements by hand, based on empirical knowledge and simple rule-of-thumb models. This people-driven planning process comes with several disadvantages. The manual creation of facility requirements is extremely labour-intensive. It therefore ties up a lot of resources which could be used otherwise. Because the process is so time-consuming and elaborate, airport planners in the past were not able to evaluate and test all theoretically possible facility requirements, but rather had to limit themselves to only creating and investigating a small number of feasible solution candidates. Consequently, it was not possible for planners to evaluate a large number of scenarios of uncertainty, simply because they did not have the tools and methods to do so.

With the introduction of the strategic capacity planning framework presented in this study, the manner in which facility requirements for airport passenger terminal facilities are evaluated and selected in practice has been fundamentally changed. This study describes a planning methodology that enables the determination of facility requirements through a *data-driven* rather than a *people-driven* process. The implications of such a data-driven process are manifold.

First, a data-driven planning process is less expensive, faster and, arguably, more precise. The labour-intensive evaluation and selection of facility requirements is delegated to a computer which can conduct such a monotonous task with greater accuracy, in less time and at a fraction of the cost that would be incurred if humans were commissioned with the planning. Moreover, to the author's best knowledge this gives practitioners the unprecedented opportunity to determine facility requirements for airport passenger terminal facilities that are truly optimal in terms of a selected index of merit, due to the fact that not only a few selected facility requirements are evaluated, but rather the entire solution space.

Secondly, the work of practitioners has been fundamentally changed by the introduction of the strategic capacity planning framework presented in this study. In the past, most planning processes in the domain of ASP were dependent on the input, knowledge, expertise and intervention of planning experts, since the necessary data basis was often very limited or was not available. For example, it was not possible to measure the DHL of specific airport passenger facilities, but airport planners were resigned to accepting approximations that were based on rough calculations and empirical knowledge. Consequently, it was almost impossible to determine strategic plans on an objective basis, as the planning methodology was firmly based on subjective opinion, individual experience and personal preference. With the introduction of a data-driven planning process, however, the roles and responsibilities of practitioners has changed fundamentally. Airport planners and decision makers can contribute their expertise and knowledge to the development, parametrisation and testing of the models, for example by selecting and designing the index of merit by which facility requirements are evaluated, as well as assessing, validating and interpreting the results. The actual preparation of plans and the decision-making, however, is done by the computer.

Finally, this study presents a new method, by means of which (big) data collected from multiple data sources by means of a PTS can be used for ASP purposes. To date, PTS data has been used exclusively in the field of tactical and operational planning of airports, for example to manage the staffing of airport passenger terminal facilities in real time (Balakrishnan et al., 2016), to monitor the performance of a facility in terms of the achieved LoS (Hansen et al., 2009), etc. To the best of the author's knowledge, this study is therefore the first to use passenger flow data collected with a PTS for an application in the field of ASP. Thus, the methods presented in this study enable the planning of ASP projects based on objective facts, mathematical models and historical evidence.

The realisation that PTS data can be used not only for operational and tactical planning purposes, but also for ASP-related applications should also be of great importance and interest to the manufacturers of PTS equipment. On the one hand, the utilisation of PTS data for strategic planning purposes represents a new use case that has not yet been recognised as such by the manufacturers. Experience shows that such companies are constantly searching for new and promising applications for data collected with their equipment. Therefore, manufacturers might be interested in promoting this use case for their own marketing purposes. On the other hand, it is quite conceivable that the application of PTS data presented in this study will also create an incentive for airports to further invest in PTS equipment. In fact, airports may be interested in improving existing PTS installations to include greater coverage areas within airport passenger terminal buildings and to improve the accuracy of measurements. Moreover, airports might be interested in using PTS equipment in facilities and processes that have not yet been within this scope.

Implications regarding facility requirements. In this study, both optimal conventional and optimal flexible facility requirements for *Check-in 1 and 3* at ZRH Airport are developed and compared. To the best of the author's knowledge, this is the first time that flexible facility requirements for airport passenger terminal facilities have been presented and simultaneously tested in an application which is relevant for ASP-related purposes. Based on the results presented in this study, it can be argued that flexible facility requirements based on decision rules represent a paradigm shift in the way strategic planning of airport (passenger terminal) facilities is conducted.

The literature on flexible ASP argues that the classical master planning process is fundamentally flawed, because neither uncertainty nor flexibility is sufficiently well considered. While uncertainty can be taken into account in strategic planning by generating large numbers of scenarios that describe how the future could evolve, flexibility can be included in ASP by means of real options. There is extensive literature on both topics. However, until now there was no tool or method available that could take into account both uncertainty and flexibility in the determination of strategic plans for airport (passenger terminal) facilities. Through the introduction of flexible facility requirements based on decision rules, the above-mentioned weaknesses of classical ASP can be remedied. Flexible facility requirements thus represent the long sought-after means by which practitioners can determine flexible strategic plans. Based on the methodology presented in this study, it is possible to consider and plan airport (passenger terminal) facilities in the context of ASP that "change easily in the face of uncertainty" (Hu & Cardin, 2015, p. 122) and are "able to modify its mode of operation or its attributes" (Saleh et al., 2002, p. 4).

From past experience, most practitioners are still used to facility requirements being specified in the form of (optimal) capacity vectors, i.e. as conventional facility requirements which define the chronological order in which future capacity adjustments are scheduled. Consequently, most strategic plans are still formulated along the lines of *how much capacity is needed* and *when must the capacity be adjusted?* This conventional way of formulating facility requirements becomes obsolete with the introduction of flexible facility requirements, since capacity vectors are the by-product of the decision rules. Therefore, the central focus of flexible facility requirements is on *how to define optimal* *decision rules*? This means that the introduction of flexible facility requirements in the domain of ASP will set out great challenges for practitioners, irrespective of whether they are airport planners, decision makers or system owners. In a first step, practitioners need to recognise that conventional facility requirements have a fundamental weakness that cannot be remedied. Indeed, it is impossible to create conventional facility requirements that can be flexibly adapted to changing circumstances. Airport planners must therefore be prepared to fundamentally change the way they define strategic planning by working with flexible facility requirements. This implies that airport planners will need further training, for instance on topics such as the creation of scenarios of uncertainty, valuation models, CEP models, etc., in order to have the methodological tools at their disposal to be able to define flexible facility requirements. For airport planners, the introduction and application of flexible facility requirements thus requires a willingness to learn.

Owners and decision makers must also be prepared and willing to apply flexible facility requirements. The practical application of flexible facility requirements in the context of ASP means that the decision-making authority of management and owners will be restricted to a certain degree. When flexible facility requirements are used, capacity adjustment decisions are no longer made by people, but by decision rules. Owners and managers should not intervene in the decision-making process, but rather have a supervisory role. On the one hand, this requires decision makers to be willing to (at least partially) relinquish their decision-making authority. On the other hand, owners and managers must also trust the decision rules. It is of no use, if, at the time a decision is made, DMs over-rule an optimal decision rule. In this case, a decision rule that is (near) optimal would be replaced with a subjectively made decision. In the event that decision makers do not trust a decision rule, it would therefore be more reasonable for the decision rule to be determined anew using the strategic capacity planning framework presented in this study. For example, such a revision of the optimal flexible facility requirements can be especially judicious if the existing decision rule(s) is/are already a few years old, or if the assumptions on which the decision rules are based have fundamentally changed.

Implications for candidate flexibilities. In this study, three different candidate flexibilities for *Check-in 1 and 3* at ZRH Airport were tested and compared in *Evaluations 1, 2 and 3*. In general, it was found that flexible facility requirements lead to a higher ENPV than comparable conventional facility requirements. One most interesting finding of this study is that not all candidate flexibilities mentioned in the literature have a positive effect on the value of a flexible engineering system or are only favourable under very specific circumstances. For instance, the results of *Evaluation 2* suggest that the planning of large modules with a size of $e_m > 1$ is only worthwhile for conventional facility requirements. For flexible facility requirements, however, the smallest possible module size should be selected so as to maximize the value of the engineering system. This implies that airport planners should not assume that the candidate flexibilities mentioned in the literature automatically increase the value of an engineering system. In any case, the benefits for the engineering system should be assessed before implementing candidate flexibilities. It is exactly for this purpose that the capacity planning framework presented in this study can be applied.

Chapter 7

Conclusion and Outlook

7.1 Conclusion

The main aim of this study was to develop, test and apply a strategic capacity planning framework which enables practitioners to determine optimal flexible and conventional facility requirements for airport passenger terminal facilities in the context of ASP. Facility requirements describe when and how the capacity of facilities should be adjusted over time to meet the expected future demand levels. The definition of facility requirements can be extraordinarily complex for several reasons. First, ASP is carried out for extremely long planning horizons ranging from 20 to 50 years, which means that it is strongly affected by uncertainty concerning potential future developments in demand, technology, politics, regulations, demographics, etc. For this reason, practitioners can only estimate how much capacity airport passenger terminal facilities will require in the future at the time of preparation of a strategic plan. Second, investments in infrastructure are (partially) irreversible. This means that once an airport passenger terminal facility has been built, the invested capital can only be salvaged to a rather limited extent. Subsequently, given the prevailing uncertainty as well as the irreversibility of investments in infrastructure, practitioners face the risk of drawing up strategic plans which turn out to be 'wrong' in hindsight and which, once investments have been made, can only be changed with great difficulty.

To mitigate this risk, the literature suggests planning engineering systems such as airport passenger terminal facilities in a flexible way. By making use of real options, which represent a "right, but not an obligation ... to do something at [*sic*] under predefined arrangements" at a future point in time, flexible engineering systems are capable of adapting to changing circumstances and needs as factors subject to uncertainty are disclosed over time (De Neufville, 2003, p. 7). For flexible engineering systems, facility requirements cannot be defined in the conventional way as capacity vectors that specify when and how the operational capacity should be adjusted. Instead, practitioners have to create so-called flexible facility requirements which make use of decision rules that describe how practitioners should best exercise the implemented real options. The literature mentions the determination of flexible facility requirements for several engineering systems, such as waste-to-energy plants or on-shore liquid natural gas production facilities. However, to the author's best knowledge, the determination of flexible facility requirements for airport passenger terminal facilities has not been covered yet.

In light of this gap in the literature, this study explores the development of a strategic capacity framework for airport passenger terminal facilities. This framework comprises of two modules: (i) a demand module, which consists of the annual aggregated demand model as well as the DHL demand model, and (ii) a CEP module, which consists of a valuation model as well as a number of conventional and flexible CEP models. The strategic capacity planning framework was applied to a real-world planning example on the existing check-in facilities at ZRH Airport. This study is divided into three research areas which cover the demand module, the CEP module and the planning example.

Research area 1 focussed on the development of demand models for both annual aggregated demand of an airport as well as passenger terminal facility-specific DHL demand. These models were necessary for the creation of the input data for the CEP models. By means of the annual aggregated demand model, which is based on GBM, large numbers of aggregated passenger demand scenarios for an airport can be created. Subsequently, these aggregated scenarios can be converted into airport passenger terminal facility-specific DHL demand scenarios by means of the DHL demand model, which is based on the ratio-method. The DHL model describes the relationship between annual aggregated demand and DHL demand with a linear regression model that considers capacity saturation of airports whose annual number of ATMs "is limited due to constraints imposed for operational, legal, environmental or political reasons" (Waltert et al., 2021, p. 2).

Research area 2 focussed on the adaptation of existing CEP models to allow them to determine the optimal conventional and optimal flexible facility requirements for airport passenger terminal facilities, based on the demand scenarios generated in research area 1. For this purpose, this study assumed that facility requirements were optimal if the ENPV of an airport passenger terminal facility were maximized over the entire planning horizon of an ASP project. Two of the CEP models presented in this study, the baseline model and the fixed model, were conventional CEP models that expressed facility requirements in terms of capacity vectors. Whereas the other two CEP models, the CGDRM and the RFDRM, were flexible models that described facility requirements by means of decision rules. The baseline model assumed that the capacity of a facility could only be changed initially. As such, the baseline model was used in this study for benchmarking purposes only, so that the results of the other CEP models could be compared with each other. The fixed model defined the optimal capacity adjustment sequence, i.e. an optimal capacity vector, for an airport passenger terminal facility over the entire planning horizon of an ASP project. The CGDRM was based on the *empirical approach*, in which the structure of a decision rule was defined in advance based on a priori knowledge of practitioners. The CGDRM was subsequently used to find the optimal parametrisation of this decision rule. The RFDRM was based on the *generative approach*, in which both the optimal structure of the decision rule and its optimal parametrisation were determined. To obtain optimal facility requirements, the baseline model employed an enumeration-based algorithm, while the other CEP models presented in this study relied on evolutionary optimization algorithms. To this end, the fixed model and the CGDRM applied the GA, while the RFDRM employed the GEP algorithm.

Research area 3 addressed the application and testing of the proposed strategic capacity planning framework by means of a real-world planning example on *Check-in 1 and 3* at ZRH Airport. The planning example has two objectives: (i) to determine whether flexible facility requirements for *Check-in 1 and 3* are economically more valuable than conventional facility requirements, as well as (ii) to identify the input factors to which the results of the CEP models are most sensitive and to quantify this influence.

To compare conventional with flexible facility requirements, three different candidate flexibilities for *Check-in 1 and 3*, referred to as *Evaluation 1, 2 and 3*, were considered. In general, the results of this study indicate that flexible system designs for *Check-in 1 and 3* are more valuable than conventional ones. However, since the evaluation model applied in this study considered exclusively cash flows that occurred during the design hours but not the entire planning period, the resulting advantage of flexible facility requirements over their conventional counterparts in terms of ENPV were somewhat lower in this study than values reported in comparable studies on flexible engineering systems. In *Evaluation 1*, which *Evaluations 2 and 3* are based on, the option to defer and the option to alter the scale were examined. The results of this study indicated that these two real options were particularly suitable to capitalise on opportunities in growing market conditions. However, once a system was built, the risks of weak market developments could only be averted and mitigated to a limited extent due to the irreversibility of investments. *Evaluation 2* considered the modular development of *Check-in 1 and 3* by means of well-defined and standardised units consisting of check-in desks as well as associated building space. This study revealed that practitioners need to select the size of modules with care in order to maximize the economic value of a system. Interestingly, for conventional facility requirements, the definition of larger module sizes proved beneficial. Whereas for flexible facility requirements, a small module size was preferable in most cases. *Evaluation 3* examined the usage of buffer spaces in airport passenger terminal facilities. Thereby, a distinction was made between buffer spaces that were temporarily used for the provision of retail services and buffer spaces which remained unused until they were converted into a fully operational airport passenger terminal facility. The results of this study suggested that the application of buffer space without retail utilisation in *Check-in 1 and 3* was only worthwhile in a market environment characterised by high growth rates. In contrast, buffer space with retail utilisation was rewarding in all market environments. However, airport planners should avoid over-designing buffer spaces with retail utilisation due to potentially high-cost premiums.

The sensitivity analysis demonstrated that facility requirements for *Check-in 1 and 3* at ZRH Airport were sensitive to changes in the discount rate, the EoS parameter, the percentage drift rate of demand, the volatility of demand as well as the average service rate. Moreover, the results indicated that the sensitivity of the CEP models used in this study was in line with the literature on flexible engineering systems.

This study contributes to knowledge in several ways. In research area 1, an ASP-specific application of GBM that allows the creation of annual aggregated demand scenarios for airports is presented. These scenarios can be converted into airport passenger terminal facility-specific DHL demand scenarios by means of a ratio-based model, which is a scientific novelty. For this reason, an article on the DHL demand model has been published in the *Journal of Air Transport Management*, see Waltert et al. (2021). Research area 2 addresses conventional and flexible CEP models specifically tailored for an application in the context of ASP for airport passenger terminal facilities. Flexible CEP models for ASP purposes are novel. Finally, research area 3 shows how the proposed strategic capacity planning framework can be applied in practice. In this context, it was shown that flexible planning is economically advantageous for *Check-in 1 and 3* at ZRH Airport.

This study has various implications. The way strategic plans for airport passenger terminal facilities are prepared is fundamentally changed by the framework presented in this study. As such, a planning methodology is suggested that enables the determination of facility requirements through a data-driven process, rather than a people-driven one.

This means that planning decisions are no longer made by humans on a subjective basis, but rather by means of mathematical models that are based on big data. For the practitioners it means that their role is redefined. They transition from a planning role to a supervisory function in which they oversee the automated planning process and provide their knowledge and expertise to the development, parametrisation and testing of the models. Planners and DMs will however have to evaluate and validate the results obtained by applying the models. However, flexible facility requirements have not yet been used in ASP. For this reason, practitioners must first be trained in the creation and application of flexible facility requirements. Finally, this study has shown that not all candidate flexibilities advertised in the literature automatically increase the value of an airport passenger terminal facility. Consequently, before implementing candidate flexibilities, practitioners are advised to always assess the merits of flexible system designs, for instance with the framework presented in this study.

7.2 Outlook

The strategic capacity planning framework presented in this study could be used either without or only with minor adaptations to determine flexible facility requirements for (i) any airport passenger terminal facility, e.g. security checkpoints or baggage carousels, (ii) any airport infrastructure, e.g. aircraft parking stands or cargo facilities, and (iii) any candidate flexibilities, e.g. shared-use facilities or temporary facilities. Moreover, the framework, or rather all models belonging to the framework, can also be applied to airports other than ZRH Airport without loss of generality. This study is the first to address flexible facility requirements for airport passenger terminal facilities in the context of ASP. Consequently, there is a large potential for further research in this area. This includes, for example, the following aspects:

(i) The decision rules used to specify flexible facility requirements can be further developed and improved. For instance, decision rules should be capable of better emulating the real-world decision-making process. In the form in which decision rules are applied in this study, only observations and information referring to planning period t are considered for decision-making. In real-world decision making, however, DMs usually also take into account both data from the past[45], i.e. information referring to planning periods $t-1, t-2, \ldots$, and forecasts for the future, i.e. data for planning periods $t+1, t+2, \ldots$. Furthermore, decision rules can be improved by further investigating which input factors, e.g. demand, costs, etc., are particularly suitable for consideration in the rules. For this purpose, the list of input factors suggested by Hu et al. (2020) may be extended accordingly. Conditional-go decision rules can be further improved by both allowing for the implementation of more complex rules, e.g. *switch-case* operators, as well as by enabling the consideration of interdependencies between engineering systems, e.g. the propagation of delays in passenger terminals. Regarding the generative approach, there is a need for research aimed at making reward functions more approachable and tangible for practitioners. Furthermore, it is conceivable that other types of mathematical and logical operators, such as *if-then-else* operators, can be implemented in the generative approach. Finally, facility requirements that are based on the empirical approach must be further compared with facility requirements that are based on the generative approach. To date, only Hu et al. (2020), Hu and Guo (2019) and this study have contributed to the scientific discourse on this topic.

(ii) As described in this study, large amounts of data originating from different sources can be merged and subsequently used for ASP purposes. The emerging potential for planning, whether at the operational, tactical or strategic level, has yet to be fully acknowledged, understood and exploited by academia as well as the aviation industry, i.e. airlines, airports, handling agents, suppliers, authorities, etc. In particular, the approach presented in this study to use (big) data for strategic planning

[45] Some studies on this extension have already been published. For example, Cardin, Xie et al. (2017) consider information regarding to planning periods $t, t-1, t-2, \ldots$ in a linear decision rule used for the strategic planning of a gasifier of a waste-to-energy plant.

can be extended by considering additional data sources, or by using new data collection methods. Additional data sources can be accessed through the exchange of data between different stakeholders in the aviation industry. Moreover, the data basis used in this study could also be expanded by integrating data collected with other or new means of measurement. For example, Waltert et al. (2021, p. 9) write, "... the usage of passenger movement data obtained through optical tracking systems would be particularly interesting, since this could offer additional insights for airport planners (e.g., dwell times, queue lengths, movement patterns, etc.)"

(iii) As explained in Section 5.1.2, this study refrained from the generation of scenarios of uncertainty for service rates of airport passenger terminal facilities, as literature on this topic is limited. Subsequently, this study can be extended by developing methods that enable the generation of such scenarios of uncertainty. These methods might consider both procedural changes at the airport passenger terminal facility in question as well as effects of technological innovation diffusion.

(iv) This study is based on an evaluation model in which the NPV of a facility is estimated based on demand during all design hours within a planning horizon. All other operating hours are explicitly not considered. By developing a ratio-based model that enables the estimation of demand not only during the design hour, but the demand for a certain airport passenger terminal facility during all operating hours, the valuation model and thereby the CEP models presented in this study could be significantly improved. Such a ratio-based model should be able to estimate the cumulative probability function describing the hourly passenger inflow into an airport passenger terminal facility, see Matthews (1995), based on both a large number of passenger flow observations as well as historic data specifying annual aggregated passenger demand of an airport.

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Appendix A

Default parametrisation of models

This appendix summarises all parameters and constraints applied in all models used the course of this study. In Appendix A.1, all parameters of the annual aggregated demand model are presented and Appendix A.2 summarises the parameters of the DHL model. The parametrisation of the NPV valuation model is summarised in and Appendix A.3 and Appendix A.4 focuses on the parametrisation of the solvers applied for the CEP model.

A.1 Annual aggregated demand model

Based on data provided in Table 5.3 on page 148, parameters μ_D, σ_D and D_0 of the annual aggregated demand model have been estimated. To this end, initial annual aggregated demand is assumed to be equal to the observed annual demand in year 2019, which is $\hat{D}_0 = 31\,478\,748\,\text{PAX}$. Moreover, percentage drift and volatility of demand growth at ZRH Airport are estimated as $\hat{\mu}_D = 3.723\,\%$ and $\hat{\sigma}_D = 2.699\,\%$. For the planning example on *Check-in 1 and 3* at ZRH Airport, i.e. *Evaluations 1, 2 and 3*, a total of $S = 5000$ annual aggregated passenger demand scenarios for ZRH Airport were created.

A.2 DHL demand model

This section provides the parametrisation applied in this study for the unsaturated DHL model and the saturated DHL model.

A.2.1 Unsaturated DHL model

The coefficients of the unsaturated DHL model have been estimated by means of the ordinary least squares method, based on 11 demand observations for ZRH Airport, see Table 5.3 on page 148. The unknown coefficients of the unsaturated DHL model are subsequently estimated as $\hat{\beta}^{US}_{CH,0} = -8.76 \times 10^4$ $(p < 0.05)$ and $\hat{\beta}^{US}_{CH,1} = 5.34 \times 10^3$ $(p < 0.05)$.

A.2.2 Saturated DHL model

The parametrisation of the saturated DHL model is as follows:

- *Coefficients of the PAXATM model.* The unknown coefficients of the PAXATM model were estimated using the ordinary least square method based on the dataset shown in Figure 4.5 on page 101. The PAXATM model fits the data (764 observations) with a coefficient of determination of $R^2 = 0.751$ and a $RSME$ of 18.6. The parameters of the PAXATM model are estimated as $\hat{\beta}^{PA}_0 = -2.52 \times 10^3$ $(p < 0.05)$, $\hat{\beta}^{PA}_1 = 4.18 \times 10^2$ $(p < 0.05)$, $\hat{\beta}^{PA}_2 = 9.72 \times 10^{-1}$ $(p < 0.05)$ and $\hat{\beta}^{PA}_3 = -1.57 \times 10^2$ $(p < 0.05)$.

- *Ratio* $\hat{r}_{CH} = 1.00$. Ratio r_{CH} is estimated on the basis of the information provided in Figure 4.6 on page 103. Because the observed values of r_{CH} shown in this figure have a high variability, it was decided to estimate ratio r_{CH} at a value of $\hat{r}_{CH} = 1.00$.

- *Maximum departure throughput capacity* $\hat{\mu}_R = 44\,\text{ATM}/\text{h}$. According to information provided by FZAG, the maximum departure throughput capacity of the runway system of ZRH Airport is equal to $\hat{\mu}_R = 44\,\text{ATM}/\text{h}$.

A.3 Valuation model

For the valuation model, a distinction is made between general parameters and parameters used for the revenue and cost functions.

A.3.1 General parametrisation

The general parametrisation of the valuation model is as follows:

- *Discount factor* $\delta = 4\,\%$. To calculate the NPV of airport infrastructure, ZRH Airport is required by the *Swiss Federal Office of Civil Aviation*, which is the competent authority in Switzerland, to apply a discount factor δ between 3.5 % to 4 % (S&P, 2019). For this study, a discount factor of $\delta = 4\,\%$ is used.

- *Operational hours per year* $h_t = 6205\,\mathrm{h}$. The NPV valuation model for airport passenger terminal facilities presented in Section 4.3 considers all costs and revenues per operating hour. In this study, it is assumed that every year consists of 365 days, during which the check-in facilities are in operation for 17 hours, i.e. from 05:00 to 22:00 local time. Consequently, every year consists of $h_t = 6205$ operating hours.

- *Maximum acceptable queuing time.* FZAG specifies the optimal temporal target LoS for the maximum waiting time of an economy class passenger during check-in as greater than or equal to $MQT_{CH}^{min} = 5\,\mathrm{min}$ and less than or equal to $MQT_{CH}^{max} = 10\,\mathrm{min}$.

- *Space per queuing passenger.* FZAG specifies the optimal spatial target LoS for the space provided per passenger queueing up in front of a check-in desk or facility as $A_{Q,CH} = 2\,\mathrm{m}^2/\,\mathrm{PAX}$.

- *Average building space required for one single check-in desk* $A_{K,CH} = 7\,\mathrm{m}^2$. According to information provided by FZAG, check-in desks currently in operation at ZRH Airport have an average length of 3.5 m and an average width of 2 m. This results in an average space requirement per check-in desk of $A_{K,CH} = 7\,\mathrm{m}^2$.

- *Average process time of check-in desk* $PT_{CH} = 60\,\mathrm{s}/\,\mathrm{PAX}$. According to information provided by FZAG, the average process or service time of a single check-in desk is $PT_{CH} = 60\,\mathrm{s}/\,\mathrm{PAX}$.

- *Average service rate of check-in desk* $\mu_{K,CH} = 60\,\mathrm{PAX}/\,\mathrm{h}$. According to information provided by FZAG, the average process or service rate of a single check-in desk is $\mu_{K,CH} = 60\,\mathrm{PAX}/\,\mathrm{h}$. Note: the service rate $\mu_{K,CH}$ is the reciprocal of the service time PT_{CH}.

A.3.2 Revenue function

The revenue function of the valuation model is parametrised as follows:

- *Unit revenues per passenger* $r_{PAX,CH} = 0.1\,\mathrm{CHF}/\,\mathrm{PAX}$. Unit revenues per passenger $r_{PAX,CH}$ describe the average revenue per passenger at *Check-in 1 and 3* at ZRH Airport. According to FZAG (2021), ZRH Airport collects an airport charge of 21 CHF/ PAX from each departing passenger. Unfortunately, the *airport charges regulation* document does not further specify in which manner the total charge is attributed to the processes and services provided to passengers (FZAG, 2021). For the purpose of this study, FZAG assumes an average revenue per passenger generated in *Check-in 1 and 3* of $r_{PAX,CH} = 0.1\,\mathrm{CHF}/\,\mathrm{PAX}$.

- *Unit revenues per check-in desk and operational hour* $r_{K,CH} = 7.06\,\mathrm{CHF}/\,\mathrm{desk}/\,\mathrm{h}$. The revenues generated by a single check-in desk during one operating hour is derived from information provided in FZAG (2021) which specifies that handling agents and airlines are charged a fee of 120 CHF per day for the usage of a single check-in desk. Consequently, assuming 365 working days per year and 6205 annual operational hours, the following average revenue per desk and hour results:

$$r_{K,CH} = \frac{120\,\mathrm{CHF} \cdot 365\mathrm{days}}{6205\,\mathrm{h}} = 7.06\,\mathrm{CHF}/\,\mathrm{desk}/\,\mathrm{h}.$$

- *Average retail, food, and beverage revenue per unit of retail area* $r_{R,CH} = 0.652$ CHF/ m^2/ h. ZRH Airport offers a total retail area of 33 200 m^2 (FZAG, 2020). Further, according to FZAG (2019), the airport generated in 2019 aggregated revenues of 114 211 000 CHF from the provision of retail services, and 20 129 000 CHF from the provision of food and beverage services. Subsequently, by diving the total revenues for retail, food and beverage by the available retail area as well as the number of operational hours per year, the average retail revenue per square metre and hour is estimated as follows:

$$r_{R,CH} = \frac{114\,211\,000\,\mathrm{CHF} + 20\,129\,000\,\mathrm{CHF}}{33\,200\,\mathrm{m}^2 \cdot 6205\,\mathrm{h}} 0.652\,\mathrm{CHF}/\,\mathrm{m}^2/\,\mathrm{h}.$$

A.3.3 Installation cost function

The installation cost function of the valuation model is parametrised as follows:

- *Unit installation costs for check-in desks* $ci^{+}_{K,CH} = 600\,000\,\mathrm{CHF}/\,\mathrm{desk}$. Based on years of operational experience, FZAG estimates the installation costs for one single check-in desk at 600 000 CHF/ desk. This figure includes both the actual installation costs of the switch and all integration costs, e.g. with the BHS.

- *Unit dismantling costs for check-in desks* $ci^{-}_{K,CH} = 2\,000\,000\,\mathrm{CHF}/\,\mathrm{desk}$. Dismantling costs include all costs incurred in the physical decommissioning of a facility. Based on years of operational experience, FZAG assumes an average unit dismantling cost of $ci^{-}_{K,CH} = 2\,000\,000\,\mathrm{CHF}/\,\mathrm{desk}$.

- *Unit installation costs for check-in area* $ci^{+}_{A,CH} = 5000\,\mathrm{CHF}/\,\mathrm{m}^2$. According to FZAG, the average installation (or construction) cost per square metre of airport passenger terminal building space is $ci^{+}_{A,CH} = 5000\,\mathrm{CHF}/\,\mathrm{m}^2$. For check-in facilities in which buffer spaces are used, see *Evaluation 3* in Section 5.4.4, a cost premium of 20 % is applied in order to cover any future integration costs with the BHS. Consequently, for buffer space area, installation costs of $ci^{+}_{A,CH} = 6000\,\mathrm{CHF}/\,\mathrm{m}^2$

apply. Note: the cost premium of 20 % applied in this study corresponds to figures reported in the literature (Cardin & Hu, 2016; Lin et al., 2013).

- *Unit dismantling costs for check-in area* $ci^{-}_{A,CH} = 50\,000\,\text{CHF}/\,\text{m}^2$. Dismantling costs include all costs incurred in the case of the physical decommission of airport passenger terminal building space. Based on years of operational experience, FZAG assumes unit dismantling costs for check-in area of $ci^{-}_{A,CH} = 50\,000\,\text{CHF}/\,\text{m}^2$.

- *Economies of scale parameter for check-in desks and building space* $\alpha_K = \alpha_A = 0.8$. According to the literature, reasonable values for α_K and α_A are in a range of 0.6 to 1 (Cardin & Hu, 2016). In this study, an EoS parameter value of $\alpha_K = \alpha_A = 0.8$ is applied.

- *Percentage overhead costs on total installation costs* $p^{ohd}_{CH} = 15\,\%$. According to FZAG, the average overhead costs for capacity expansion projects at ZRH Airport correspond to approximately 15 % of the total expenses of a project.

- *Percentage of circulation space on total facility space* $p^{circ}_{CH} = 57.8\,\%$. According to an evaluation carried out by FZAG, 57.8 % of the area of the existing check-in facilities at ZRH Airport is used for circulation.

A.3.4 Operational cost function

The operational cost function of the valuation model is parametrised as follows:

- *Unit operating costs per check-in desk* $co_{K,CH} = 0.345\,\text{CHF}/\,\text{desk}/\,\text{h}$. To estimate the unit operating costs of a check-in desk, FZAG assumes that a total of 5 full time equivalents (FTEs) are required to maintain all 210 check-in desks currently in operation at ZRH Airport. Under the assumption of yearly salary costs and social security contributions of 90 000 CHF per FTE and 6205 annual operating hours,

$co_{K,CH}$ is calculated as:

$$co_{K,CH} = \frac{5\,\text{FTE} \cdot 90\,000\,\text{CHF/yr}}{210\,\text{desks} \cdot 6205\,\text{h/yr}} = 0.345\,\text{CHF/desk/h}.$$

- *Unit operating costs per unit of check-in facility space* $co_{A,CH} = 0.011\,\text{CHF/m}^2\text{/h}$. FZAG assumes that 10 FTEs are required to maintain and clean the total check-in area installed at ZRH Airport, which is $13\,272\,\text{m}^2$, resulting in an average unit operating cost $co_{A,CH}$ of:

$$co_{A,CH} = \frac{10\,\text{FTE} \cdot 90\,000\,\text{CHF/yr}}{13\,272\,\text{m}^2 \cdot 6205\,\text{h/yr}} = 0.011\,\text{CHF/m}^2\text{/h}.$$

- *Unit operating costs per unit of buffer space* $co_R = 0.05\,\text{CHF/m}^2\text{/h}$. Operating costs for buffer space include costs for maintenance and cleaning. The value used for co_R is based on an assumption made by FZAG.

- *Unit operating costs per unit of demand* $co_{d,CH} = 0\,\text{CHF/PAX}$. According to FZAG, no unit operating costs per passenger co_d are incurred.

A.3.5 Penalty cost function

The parametrisation of the penalty cost function was determined in a *trial-and-error* process. The application of such a *trial-and-error* process is in line with the recommendations of Saffarzadeh and Braaksma (2000). The penalty cost function of the valuation model applied in this study is parametrised as follows:

- *Provision of one over-designed check-in desk* $cp^{\lceil}_{CH} = 5\,\text{CHF/desk/h}$. FZAG assumes a penalty cost of 5 CHF per hour for every over-designed check-in desk. The selected value for $cp^{\lceil}_{CH}$ is based on an assumption.

- *Provision of one under-designed check-in desk* $cp^{\lfloor}_{CH} = 25\,\text{CHF/desk/h}$. FZAG assumes a penalty cost of 25 CHF per hour for every over-designed check-in desk.

The selected value for $cp_{CH}^{\lceil}$ is based on an assumption. Note: the penalty costs for operating the facility with under-designed capacity was deliberately chosen to be higher than the penalty costs for operating the facility with over-designed capacity. The reason for this decision is that in a facility with under-designed capacity, the probability of congestion and delays is greater than in a facility that is over-designed.

- *Coefficient* $\alpha_P = 1.2$. The coefficient α_P in the penalty cost function is used to model non-linear effects between the provision of capacity and the resulting levels of delay. For this study, the value of the coefficient was set to $\alpha_P = 1.2$.

A.4 CEP models and solvers

The constraints applied to solve the proposed CEP models are summarised in Table A.1. Table A.2 contains all parameters applied for the GA applied to solve the fixed model and the CGDRM as well as the GEP used to solve the RFDRM.

	Evaluation 1 and 3	*Evaluation 2*
Baseline Model	$-K_{CH,0} \leq \Delta K_{CH,0} \leq 1000$ desks	$-K_{CH,0} \leq \Delta K_{CH,0} \leq 1000$ desks
Fixed Model	-50 desks $\leq \Delta K_{CH,t} \leq -50$ desks	$\Delta K_{CH,t} \theta_1, \theta_2$ and e_l are restricted for *Evaluation 2* as follows: they are either 0 desks, $\pm e_m$ desks or a multiple of $\pm e_m$ desks, but not larger than 50 desks and not less than -50 desks.
CGDRM	-50 desks $\leq \theta_1, \theta_2 \leq -50$ desks	
RFDRM	$e_l = \{-50, -49, \ldots, 50\}$	

Table A.1: Constraints applied to CEP models presented in this study.

	Fixed Model	CGDRM	RFDRM
Solver	*eaSimple* solver provided in the *DEAP* package, version 1.3	*eaSimple* solver provided in the *DEAP* package, version 1.3	*gep_simple* solver provided in the *GEPPY* package, version 0.1.2
Population size	150 chromosomes	150 chromosomes	150 chromosomes
Length of chromosome	20 genes	2 genes	19 genes, length of head of chromosomes: 8 genes, length of tail of chromosomes: 9 genes, maximum arity: 2
Selection operator(s)	Tournament selection, tournament size = 4. Elitism for best performing solution candidate	Tournament selection, tournament size = 4. Elitism for best performing solution candidate	Tournament selection, tournament size = 4. Elitism for best performing solution candidate
Crossover operator(s)	Two point crossover	One point crossover	Combination of one point and two point crossover
Mutation operator(s)	Uniform mutation operator, mutation probability: 5 %	Uniform mutation operator, mutation probability: 5 %	Uniform mutation operator, mutation probability: 5 %
Transposition operator(s)	-	-	IS and RIS transposition with probability 10 % each, no gene transposition operator used
Termination condition	100 generations, based on evaluation of solution performance, see Section 5.5.	20 generations, based on evaluation of solution performance, see Section 5.5.	50 generations, based on evaluation of solution performance, see Section 5.5.

Table A.2: Parametrisation of GA and GEP solvers used for fixed model, CGDRM and RFDRM.

Appendix B

Supplementary results

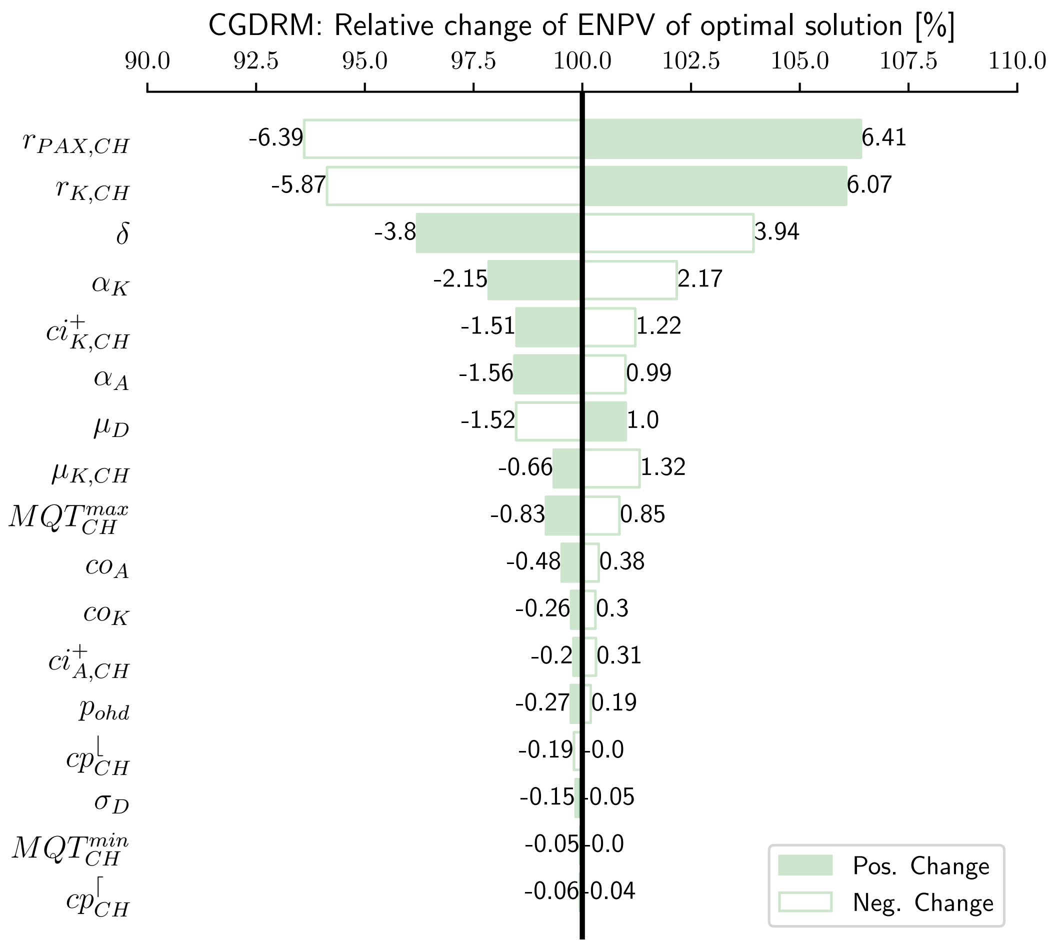

Figure B.1: Tornado diagram depicting the results of a sensitivity analysis carried out for the CGDRM for *Check-in 1 and 3* and *Evaluation 1*.

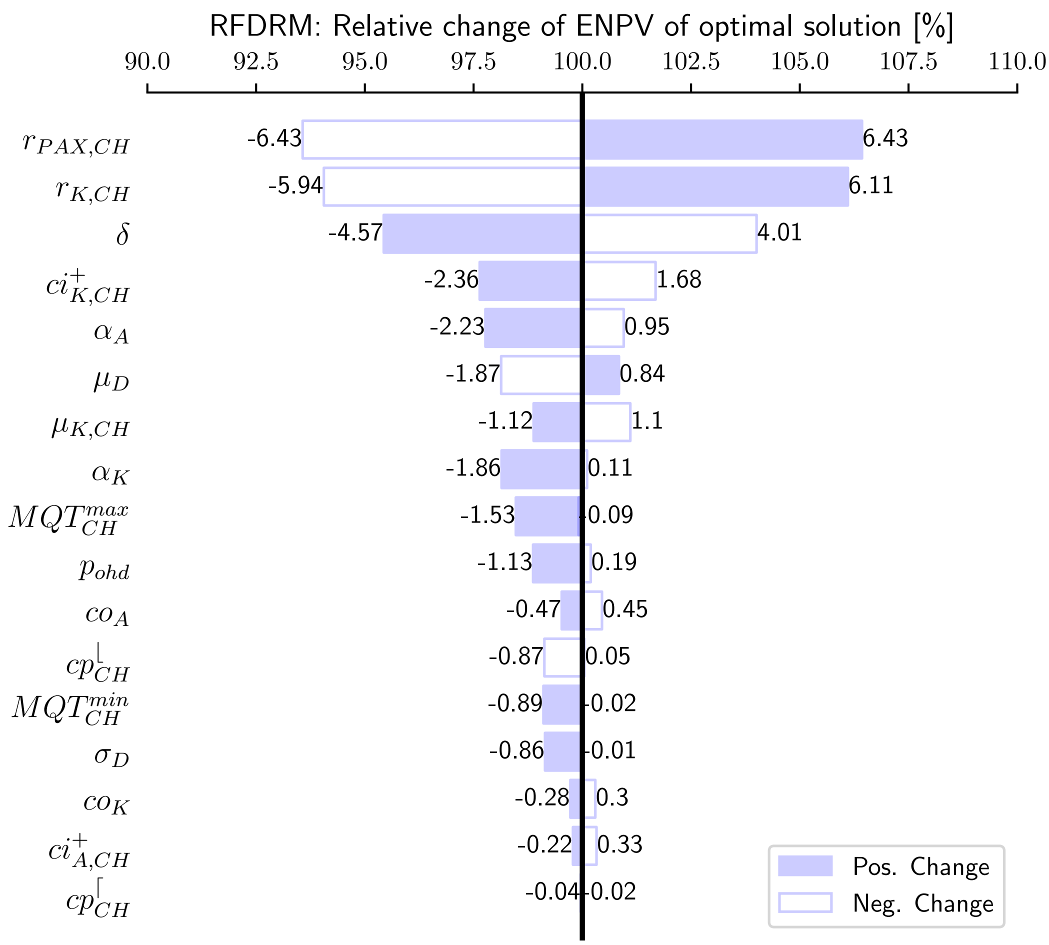

Figure B.2: Tornado diagram depicting the results of a sensitivity analysis carried out for the RFDRM for *Check-in 1 and 3* and *Evaluation 1*.

Model	Run	Optimal Solution	ENPV
Baseline	1	$\Delta K^{*}_{CH,0} = 28$	10 557.0
	2	$\Delta K^{*}_{CH,0} = 28$	10 557.0
	3	$\Delta K^{*}_{CH,0} = 28$	10 557.0
	4	$\Delta K^{*}_{CH,0} = 28$	10 557.0
	5	$\Delta K^{*}_{CH,0} = 28$	10 557.0
Fixed Model	1	$\mathbf{K}^{*}_{CH} = [\,57,64,65,65,69,72,73,74,76,76,76,76,77,80,80,84,84,84,90,90\,]$	10 580.3
	2	$\mathbf{K}^{*}_{CH} = [\,59,64,64,64,65,65,67,69,76,77,79,79,79,80,86,87,88,88,89,93\,]$	10 484.4
	3	$\mathbf{K}^{*}_{CH} = [\,59,59,59,63,63,71,76,78,81,83,83,83,83,83,83,83,83,85,85,85\,]$	10 901.3
	4	$\mathbf{K}^{*}_{CH} = [\,56,63,64,65,67,70,70,70,75,75,79,79,81,81,81,81,82,83,84,84\,]$	10 747.7
	5	$\mathbf{K}^{*}_{CH} = [\,53,59,60,62,66,69,69,71,75,75,75,75,84,85,85,85,86,86,87,87\,]$	10 791.2
CGDRM	1	$\boldsymbol{\theta}^{*} = [11,-2]$	11 139.0
	2	$\boldsymbol{\theta}^{*} = [9,-1]$	11 153.9
	3	$\boldsymbol{\theta}^{*} = [7,-1]$	11 180.7
	4	$\boldsymbol{\theta}^{*} = [7,-1]$	11 180.7
	5	$\boldsymbol{\theta}^{*} = [12,-1]$	11 153.2
RFDRM	1	$\mathcal{L}^{*} = \frac{(K^{s}_{i,t-1} - d^{s}_{i,t})}{K^{s}_{i,t-1} * e_l + d^{s}_{i,t}}$	11 159.2
	2	$\mathcal{L}^{*} = \frac{K^{s}_{i,t-1} * (K^{s}_{i,t-1} - e_l)}{(K^{s}_{i,t-1} - d^{s}_{i,t})}$	11 022.9
	3	$\mathcal{L}^{*} = \frac{K^{s}_{i,t-1}}{K^{s}_{i,t-1} - d^{s}_{i,t} * (e_l^2 + 1)}$	11 158.8
	4	$\mathcal{L}^{*} = \frac{K^{s}_{i,t-1} * d^{s}_{i,t}}{K^{s}_{i,t-1} - d^{s}_{i,t}}$	11 022.9
	5	$\mathcal{L}^{*} = \frac{-K^{s}_{i,t-1} * d^{s}_{i,t}}{-K^{s}_{i,t-1} * (K^{s}_{i,t-1} - d^{s}_{i,t}) + e_l^2}$	11 026.6

Table B.1: Optimal conventional and flexible facility requirements for *Evaluation 1* determined in 5 independent executions of the solvers of the baseline model, the fixed model, the CGDRM and the RFDRM. ENPV figures are provided in CHF.

	Model	e_m	α	ENPV	min	max	VaG	VaR	VoF
$e_m = 1$	Fixed	1	0.8	10 761	8112	11 308	11 108	10 250	183
	CGDRM	1	0.8	**11 190**	**9549**	**12 008**	**11 593**	10 714	**612**
	RFDRM	1	0.8	11 126	9515	11 917	11 483	**10 727**	549
e_m^*	Fixed	16	0.8	11 150	8273	11 774	11 520	10 612	572
	CGDRM	17	0.8	11 190	**9549**	12 008	11 593	**10 714**	612
	RFDRM	17	0.8	**11 194**	9290	**12 115**	**11 645**	10 655	**617**
$e_m = 1$	Fixed	1	1.0	9733	6995	10 373	10 109	9204	821
	CGDRM	1	1.0	10 019	8749	10 787	10 308	9712	1107
	RFDRM	1	1.0	**10 215**	**8950**	**10 858**	**10 484**	**9912**	**1303**
e_m^*	Fixed	4	1.0	9929	7394	10 502	10 262	9449	1017
	CGDRM	1	1.0	10 019	8749	10 787	10 308	9711	1107
	RFDRM	1	1.0	**10 215**	**8950**	**10 858**	**10 484**	**9912**	**1303**

Table B.2: Simulation results for *Evaluation 2* for module size $e_m = 1$ and e_m^*. EoS parameters $\alpha_K = \alpha_A = 0.8, 1.0$ and discount rate $\delta = 0.04$. All other parameters are default. ENPV, min, max, VaG, VaR and VoF figures are provided in CHF.

	Model	e_m	α	ENPV	min	max	VaG	VaR	VoF
$e_m = 1$	Fixed	1	0.8	5533	4427	5843	5708	5295	612
	CGDRM	1	0.8	**5795**	5156	**6075**	**5924**	5657	**874**
	RFDRM	1	0.8	5778	**5174**	6005	5879	**5665**	857
e_m^*	Fixed	7	0.8	5674	4425	5967	5837	5440	753
	CGDRM	1	0.8	**5795**	5156	**6075**	**5924**	5657	**874**
	RFDRM	1	0.8	5778	**5174**	6005	5879	**5665**	857
$e_m = 1$	Fixed	1	1.0	5064	3940	5386	5243	4823	965
	CGDRM	1	1.0	5241	4570	5566	5330	5146	1141
	RFDRM	1	1.0	**5356**	**4957**	**5648**	**5432**	**5280**	**1257**
e_m^*	Fixed	2	1.0	5065	3884	5333	5234	4830	966
	CGDRM	4	1.0	5241	4899	5531	5329	5158	1142
	RFDRM	1	1.0	**5356**	**4957**	**5648**	**5432**	**5280**	**1257**

Table B.3: Simulation results for *Evaluation 2* for module size $e_m = 1$ and e_m^*. EoS parameters $\alpha_K = \alpha_A = 0.8, 1.0$ and discount rate $\delta = 0.12$. All other parameters are default. ENPV, min, max, VaG, VaR and VoF figures are provided in CHF.

		$e_m = 5$ ENPV	VoF	$e_m = 10$ ENPV	VoF	$e_m = 20$ ENPV	VoF	$e_m = 30$ ENPV	VoF
$\alpha = 0.7$	Baseline	11 051		11 051		11 051		11 051	
	Fixed	11 426	375	11 469	418	11 358	308	**11 335**	**284**
	CGDRM	11 510	459	**11 510**	**459**	**11 483**	**433**	11 277	227
	RFDRM	**11 512**	**462**	11 501	450	11 442	392	11 177	126
$\alpha = 1.0$	Baseline	8912		8912		8912		8912	
	Fixed	9887	975	**9779**	**867**	8721	−191	**9151**	**238**
	CGDRM	**9983**	**1070**	9634	722	**8968**	**56**	8728	−184
	RFDRM	9928	1016	9555	643	8810	−102	8754	−159
$\delta = 0.04$	Baseline	9892		9892		9892		9892	
	Fixed	10 483	590	**10 557**	**665**	10 021	128	**10 211**	**319**
	CGDRM	**10 641**	**748**	10 482	590	**10 173**	**280**	9985	93
	RFDRM	10 619	727	10 414	521	10 155	263	9859	−33
$\delta = 0.12$	Baseline	4510		4510		4510		4510	
	Fixed	5336	826	5180	670	4928	418	**4777**	**267**
	CGDRM	**5531**	**1022**	5391	882	**5018**	**509**	4743	234
	RFDRM	5496	987	**5403**	**894**	4741	231	4247	−262

Table B.4: Simulation results for *Evaluation 2*. EoS parameter value $\alpha = 0.7, 1.0$ and discount rate $\delta = 0.04, 0.12$. All other parameters are default. ENPV and VoF figures are provided in CHF.

		$e_m = 5$		$e_m = 10$		$e_m = 20$		$e_m = 30$	
		ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF
$\mu_D = 0.04$	Baseline	10 526		10 526		10 526		10 526	
	Fixed	10 905	380	10 961	435	10 809	283	**10 819**	**293**
	CGDRM	11 150	624	**11 150**	**624**	**11 037**	**512**	10 693	168
	RFDRM	**11 168**	**643**	11 149	**624**	11 029	504	10 641	115
$\mu_D = 0.12$	Baseline	11 623		11 623		11 623		11 623	
	Fixed	12 390	767	**12 675**	**1052**	**12 863**	**1240**	12 776	1153
	CGDRM	**12 611**	**988**	12 611	988	12 611	988	12 607	985
	RFDRM	12 345	722	12 582	959	12 569	946	**12 827**	**1204**
$\sigma_D = 0.04$	Baseline	10 526		10 526		10 526		10 526	
	Fixed	10 905	380	10 961	435	10 809	283	**10 819**	**293**
	CGDRM	11 150	624	**11 150**	**624**	**11 037**	**512**	10 693	168
	RFDRM	**11 168**	**643**	11 149	**624**	11 029	504	10 641	115
$\sigma_D = 0.12$	Baseline	8657		8657		8657		8657	
	Fixed	8819	162	8955	299	8761	105	8785	128
	CGDRM	10 296	1640	**10 296**	**1640**	**10 112**	**1455**	**9744**	**1088**
	RFDRM	**10 346**	**1690**	10 207	1550	10 074	1418	9650	993

Table B.5: Simulation results for *Evaluation 2*. Percentage drift rate of demand $\mu_D = 0.04, 0.2$ and demand volatility $\sigma_D = 0.04, 0.12$. All other parameters are default. ENPV and VoF figures are provided in CHF.

		$e_m = 5$		$e_m = 10$		$e_m = 20$		$e_m = 30$	
		ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF
$\mu_{K,CH} = 50$	Baseline	10 857		10 857		10 857		10 857	
	Fixed	11 328	471	**11 382**	**525**	11 130	273	10 932	76
	CGDRM	**11 544**	**687**	11 293	436	**11 282**	**426**	**11 211**	**354**
	RFDRM	11 192	335	11 312	456	11 269	412	11 204	347
$\mu_{K,CH} = 70$	Baseline	10 451		10 451		10 451		**10 451**	
	Fixed	10 913	462	10 964	513	10 892	441	10 266	−185
	CGDRM	10 998	546	10 977	526	**10 977**	**526**	10 436	**−15**
	RFDRM	**11 019**	**568**	**11 015**	**564**	10 903	452	10 243	−209

Table B.6: Simulation results for *Evaluation 2*. Average service rate of check-in desk $\mu_{K,CH} = 50, 70$ passengers per hour. All other parameters are default. ENPV and VoF figures are provided in CHF.

		Buffer space without retail utilisation						Buffer space with retail utilisation					
		750 m^2		1500 m^2		3000 m^2		750 m^2		1500 m^2		3000 m^2	
		ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF
$\mu_D = 0.04$	Baseline	10 016		9380		8026		**16 663**		**22 674**		**34 614**	
	Fixed	10 564	548	10 066	686	8815	789	12 770	−3893	17 581	−5093	29 563	−5050
	CGDRM	**10 986**	**970**	**10 646**	**1265**	**9357**	**1331**	13 271	−3392	18 182	**−4493**	30 164	−4450
	RFDRM	10 890	874	10 464	1084	9149	1123	13 348	**−3315**	18 182	**−4493**	30 167	**−4447**
$\mu_D = 0.12$	Baseline	11 113		10 604		9349		**17 760**		**23 897**		**35 937**	
	Fixed	12 072	959	12 029	1425	11 200	1850	12 818	−4942	15 173	−8725	25 269	−10 668
	CGDRM	**12 684**	**1571**	**12 510**	**1906**	**11 782**	**2433**	13 092	**−4668**	15 443	**−8455**	25 631	**−10 306**
	RFDRM	12 124	1011	11 951	1347	11 063	1714	12 872	−4888	15 396	−8502	25 509	−10 427
$\sigma_D = 0.04$	Baseline	10 016		9380		8026		**16 663**		**22 674**		**34 614**	
	Fixed	10 564	548	10 066	686	8815	789	12 770	−3893	17 581	−5093	29 563	−5050
	CGDRM	**10 986**	**970**	**10 646**	**1265**	**9357**	**1331**	13 271	−3392	18 182	**−4493**	30 164	−4450
	RFDRM	10 890	874	10 464	1084	9149	1123	13 348	**−3315**	18 182	**−4493**	30 167	**−4447**
$\sigma_D = 0.12$	Baseline	8147		7501		6148		**14 794**		**20 795**		**32 736**	
	Fixed	8454	307	8089	588	6795	647	10 438	−4356	15 829	−4966	27 784	−4952
	CGDRM	10 050	1903	9604	2103	8344	2196	12 772	−2022	17 751	−3044	29 708	−3027
	RFDRM	**10 158**	**2011**	**9698**	**2196**	**8420**	**2272**	12 862	**−1932**	17 789	**−3006**	29 718	**−3017**

Table B.7: Simulation results for *Evaluation 3*. Percentage drift rate of demand $\mu_D = 0.04, 0.2$ and demand volatility $\sigma_D = 0.04, 0.12$. All other parameters are default. ENPV and VoF figures are provided in CHF.

		Buffer space without retail utilisation						Buffer space with retail utilisation					
		750 m^2		1500 m^2		3000 m^2		750 m^2		1500 m^2		3000 m^2	
		ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF
$\alpha = 0.8$	Baseline	10 634		10 061		8892		**17 281**		**23 355**		**35 480**	
	Fixed	11 121	486	10 760	699	9676	784	13 224	–4057	17 949	–5406	30 231	–5249
	CGDRM	**11 594**	**960**	**11 300**	**1239**	**10 188**	**1296**	13 664	**–3617**	18 551	**–4803**	30 707	**–4773**
	RFDRM	11 186	552	10 807	746	10 039	1147	13 605	–3676	18 462	–4893	30 617	–4863
$\alpha = 1.0$	Baseline	8402		7343		4656		**15 049**		**20 637**		**31 244**	
	Fixed	9472	1070	8666	1323	5926	1270	11 582	–3467	16 093	–4544	26 706	–4538
	CGDRM	9552	1151	8704	1361	6036	1380	11 987	–3062	16 416	–4221	27 023	–4220
	RFDRM	**9754**	**1352**	**8857**	**1514**	**6176**	**1520**	12 173	**–2875**	16 537	**–4100**	27 144	**–4099**
$\delta = 0.04$	Baseline	8402		7343		4656		**15 049**		**20 637**		**31 244**	
	Fixed	9472	1070	8666	1323	5926	1270	11 582	–3467	16 093	–4544	26 706	–4538
	CGDRM	9552	1151	8704	1361	6036	1380	11 987	–3062	16 416	–4221	27 023	–4220
	RFDRM	**9754**	**1352**	**8857**	**1514**	**6176**	**1520**	12 173	**–2875**	16 537	**–4100**	27 144	**–4099**
$\delta = 0.12$	Baseline	4295		3153		847		**8459**		**11 481**		**17 502**	
	Fixed	5248	953	4290	1137	1923	1077	7206	–1253	9971	–1509	16 013	–1489
	CGDRM	5409	1114	4472	1319	2172	1325	7423	–1036	10 101	–1380	16 122	–1380
	RFDRM	**5539**	**1244**	**4586**	**1433**	**2281**	**1435**	7515	**–944**	10 161	**–1320**	16 182	**–1320**

Table B.8: Simulation results for *Evaluation 3*. EoS parameter value $\alpha = 0.8, 1.0$ and discount rate $\delta = 0.04, 0.12$. All other parameters are default. ENPV and VoF figures are provided in CHF.

		Buffer space without retail utilisation						Buffer space with retail utilisation					
		750 m^2		1500 m^2		3000 m^2		750 m^2		1500 m^2		3000 m^2	
		ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF	ENPV	VoF
$\mu_K = 50$	Baseline	10 426		9850		8477		**17 073**		**23 144**		**35 065**	
	Fixed	10 926	500	10 662	812	9314	836	12 438	−4635	15 971	−7173	28 135	−6930
	CGDRM	**11 503**	**1076**	**11 220**	**1369**	**10 001**	**1524**	12 986	**−4087**	17 048	−6096	29 010	−6055
	RFDRM	11 371	945	10 789	938	9842	1365	12 912	−4161	17 108	**−6036**	29 051	**−6014**
$\mu_K = 70$	Baseline	10 012		9338		7993		**16 658**		**22 631**		**34 581**	
	Fixed	10 717	705	10 247	910	9003	1010	12 435	−4224	17 853	−4779	30 206	−4375
	CGDRM	**10 884**	**872**	**10 425**	**1087**	**9125**	**1131**	13 339	**−3319**	18 701	**−3930**	30 690	**−3891**
	RFDRM	10 801	789	10 312	975	9007	1013	13 310	−3348	18 596	−4035	30 584	−3997

Table B.9: Simulation results for *Evaluation 3*. Average service rate of check-in desk $\mu_{K,CH} = 50, 70$ passengers per hour. All other parameters are default. ENPV and VoF figures are provided in CHF.

Appendix C

Software documentation

The software required for the annual aggregated demand model introduced in Section 4.1 and the DHL demand model presented in Section 4.2 is written in the *Python* programming language (version 3.7.7). An overview of the structure of the software is given in Figure C.1.

The baseline model, the fixed model, the CGDRM and the RFDRM, which are described in Section 4.4, are also written in the *Python* programming language (version 3.7.7). The solver of the baseline model, which is based on the enumeration technique, is written by the author. The fixed model and the CGDRM are solved near-optimally with the *eaSimple* GA solver provided in the *DEAP* package, version 1.3 (Fortin et al., 2012). The RFDRM is near-optimally solved with the *gep_simple* GEP solver provided in the *GEPPY* package, version 0.1.2 (Gao, 2018). An overview of the structure of the software for the CEP models presented in this study is given in Figure C.2. Please note, the software used for this study is published in the following repository: https://github.zhaw.ch/wate/StrategicCapacityFramework.

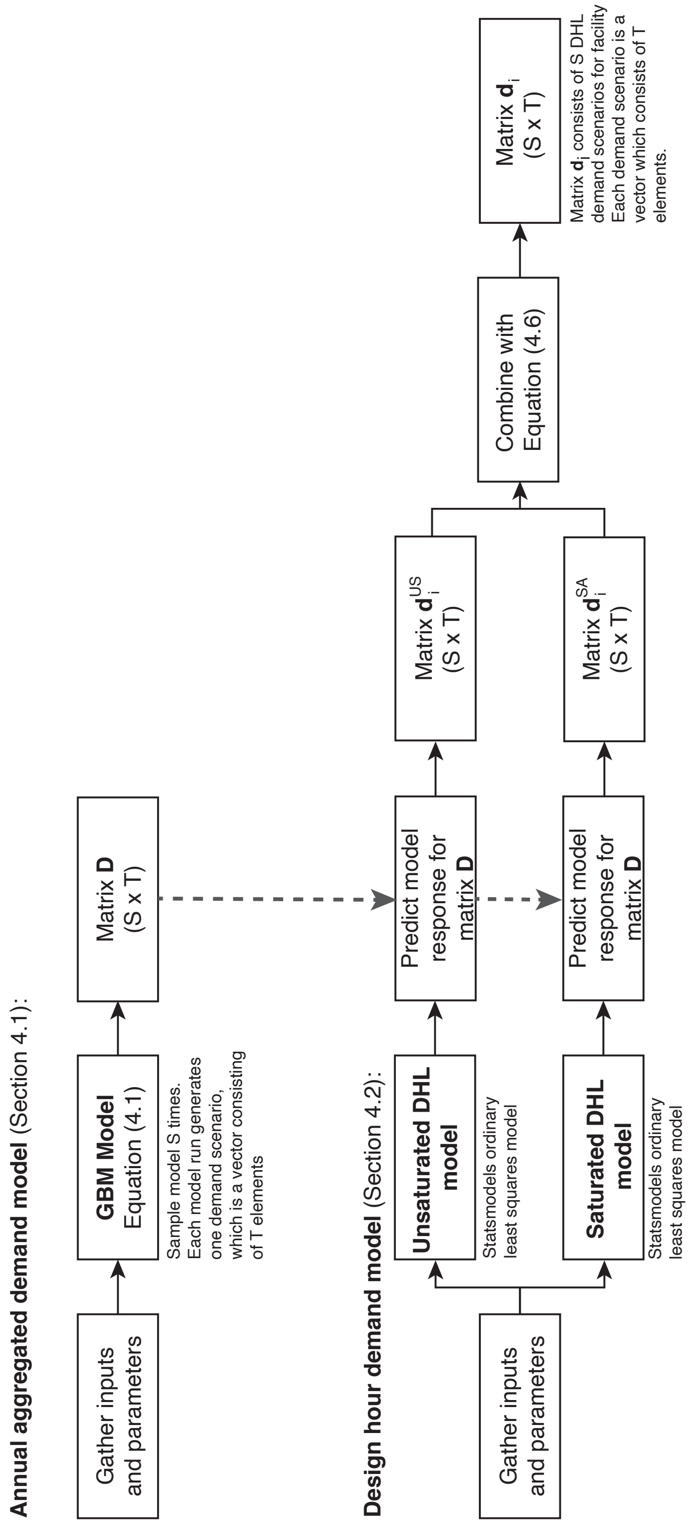

Figure C.1: Software structure of annual aggregated demand model and DHL demand model.

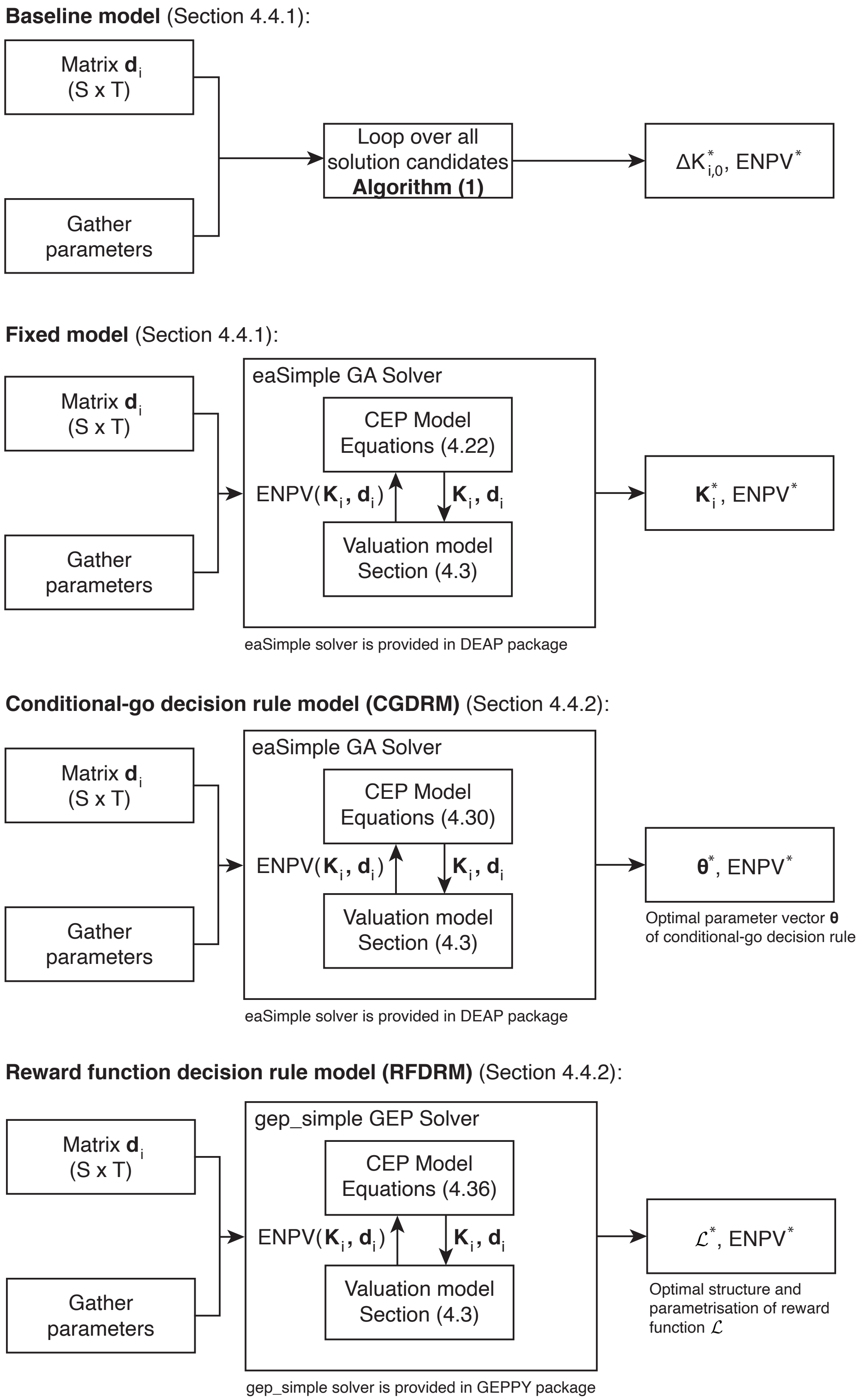

Figure C.2: Software structure of conventional and flexible CEP models developed and implemented in this study.