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OPTIMIZATION MODELS FOR THE EXPANSION OF AIRPORT NETWORKS

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Abstract

Demand for air transportation has grown very rapidly over the last few decades. This growth can be explained by a generalized increase of population and purchasing power, international business and trade, and also by technological improvements. The growth in demand has not been accompanied with an adequate increase of airport capacity, and this has led to the escalation of congestion problems at many airports worldwide. The airport congestion problems manifest themselves primarily in the form of delays. These delays and their propagation throughout the network have negative impacts on air transportation level of service, on passenger quality of travel, and, more broadly, on economic activity.

Because air transportation is vital for economic activity, there is a need to find ways by which the air transportation system continues to be reliable and meets the increase of demand – it is, thus, important to find solutions to solve the congestion problems at the airports. In the short term, part of these problems can be dealt with through demand management mechanisms. In the longer term, improvements in air traffic control systems will certainly further contribute to attenuate them. However, it is unlikely that airport congestion can be fully coped with if the capacity of existing airports is not expanded and/or new airports are not built.

There are a significant number of (academic) studies dealing with airport expansion and/or location problems, but they focus on individual airports. Studies dealing with

airport expansion and/or construction problems from a network perspective are uncommon. This is especially true for the optimization-based literature. This thesis attempts to contribute to this literature by presenting a set of optimization models – from static and deterministic to dynamic and stochastic – for assisting aviation authorities in their strategic reflections regarding the expansion of airport networks. The models apply to a set of metropolitan areas and seek the best improvements to apply to the respective airport network in order to serve demand in the best possible way, for a given budget. The improvements to the airport network are chosen from a set of feasible expansion actions. Expansion actions consist in improvements to the existing airports (through the reconfiguration and/or construction of runways and through the enhancement of terminal buildings) and in the construction of new airports. The objective of the models is to maximize total system throughput (maximize demand "coverage"), taking into account the impact of airport capacity increase on travel costs and travel demand. The models developed are complex mixed-integer nonlinear optimization models, being difficult to solve to exact optimality. Therefore, several heuristic methods are proposed to solve the models. Their performance, from the standpoint of solution quality and computational effort, are compared through their application to a large sample of randomly generated test instances.

The practical usefulness of the models is illustrated with applications to the main airport networks of the United States of America and Germany.

Resumo

A procura de transporte aéreo tem crescido de forma significativa nas últimas décadas. Este crescimento pode ser explicado pelo aumento generalizado de população e poder de compra, trocas comerciais entre países, e também por desenvolvimentos tecnológicos. O crescimento da procura não tem sido acompanhado por um aumento adequado de capacidade aeroportuária, o que tem conduzido ao aumento de problemas de congestionamento em vários aeroportos. Os problemas de congestionamento nos aeroportos manifestam-se sobretudo na forma de atrasos. Os atrasos e a sua propagação pela rede de aeroportos têm um impacto negativo na qualidade de serviço, na comodidade de viagem do passageiro, e na atividade económica.

Uma vez que o transporte aéreo tem uma grande importância na atividade económica, é necessário que o sistema de transporte aéreo continue seguro e capaz de satisfazer o aumento de procura – é, por isso, importante encontrar soluções que permitam resolver os problemas de congestionamento dos aeroportos. No curto prazo estes problemas podem ser abordados através de mecanismos de gestão de procura, e em prazos mais longos podem ser parcialmente atenuados através do melhoramento dos sistemas de controlo do tráfego aéreo. No entanto, é pouco plausível que o congestionamento dos aeroportos possa ser eliminado sem que capacidade dos aeroportos existentes seja aumentada e sem que sejam construídos novos aeroportos.

Existe um grande número de estudos (académicos) que abordam problemas de expansão e/ou construção de aeroportos, mas focam-se em aeroportos individuais. Estudos que abordam problemas de expansão e/ou construção de aeroportos numa perspetiva de rede são incomuns, especialmente na literatura de otimização. Esta tese pretende contribuir para esta literatura através de um conjunto de modelos de otimização – de estáticos e determinísticos a dinâmicos e estocásticos – destinados a apoiar as autoridades de transporte aéreo nas suas decisões estratégicas relativas à expansão de redes de aeroportos. Os modelos aplicam-se a um conjunto de áreas metropolitanas e procuram determinar os melhoramentos a realizar na respetiva rede de aeroportos de forma a servir a procura da melhor forma possível em função do orçamento disponível. Estes melhoramentos são escolhidos de entre um conjunto de ações possíveis de expansão, que podem incidir nos aeroportos existentes (através da reconfiguração e/ou construção de pistas e através da beneficiação de terminais) ou consistir na construção de novos aeroportos. O objetivo dos modelos é maximizar o tráfego total na rede de aeroportos (maximizar a "cobertura" da procura), considerando o impacto dos aumentos de capacidade aeroportuária no custo e na procura de transporte aéreo. Os modelos de otimização apresentados são não-lineares e inteiros mistos, pelo que são difíceis de resolver de forma exata. Deste modo, são propostos vários métodos heurísticos para resolver os modelos. O respetivo desempenho é avaliado, relativamente à qualidade das soluções e ao esforço computacional, com base nos resultados obtidos para um número significativo de instâncias-teste de várias dimensões.

A utilidade prática dos modelos propostos é evidenciada através de aplicações às redes de aeroportos principais dos Estados Unidos da América e da Alemanha.

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Chapter 1

Introduction

Transportation has played an important role in the development of civilizations by meeting the mobility needs of people and goods. Air transportation in particular has had a major impact on economic and social development (Plessis-Fraissard 2004). The airline industry has grown tremendously over the last few decades, instigated by the increase in demand for air transportation services that economic progress and globalization, as well as the liberalization of governmental regulations, have motivated (de Neufville and Odoni 2003). Despite the large investments that have been made in infrastructure, particularly in airports, these have been insufficient to meet the growth in demand, and congestion problems, in the form of flight delays and disruptions, have escalated in many airports worldwide.

This introductory chapter starts with a description of air transportation trends with a focus on airport congestion and a presentation of the types of measures that can be taken to deal with it. Then, we address airport capacity expansion decisions mentioning some important research work that deal with this topic. In the final part of the chapter, we present the thesis' objectives and structure, and identify activities carried out or to carry out for the dissemination of this research.

1. Air transportation trends

Demand for air transportation has grown very rapidly over the last few decades. This growth can be explained by a generalized increase of population and purchasing power, international business and trade, and also by technological improvements – reducing the cost of operations, and increasing the reliability of aircrafts and of related infrastructure such as air traffic control and navigational aids (Nanayakkara 2008).

The growth of demand for air transportation differs across the regions of the world, depending on the life cycle stage of the respective airline industry. The life cycle of airline industry can be represented with an S-shaped curve, in which there are low growth rates at the initial stage, rapid growth rates at the intermediate stage, and again low growth rates at the mature stage. According to Bonnefoy and Hansman (2008), which gathered data from the International Civil Aviation Organization (ICAO) and the International Air Transport Association (IATA) for the period between 1987 and 2007, the airline industry in North America and Western Europe is considered to be reaching a mature stage, presenting growth rates of 5.7% and 5.0% respectively, whereas the Asia-Pacific and Middle-East regions are considered to be undergoing the rapid growth stage, with a growth rate of 8.8% in the former case for the same period, and 13% in the latter case for the period between 2000 and 2007.

The growth in the number of aircraft operations together with the relatively slow increase of airport capacity have led to the escalation of congestion problems at many airports worldwide. The airport congestion problems manifest themselves in the form of delays, both on the ground and in the air as takeoffs and landings have to be held up. For example, in the United States (US), and despite the increase of scheduled travel times, the percentage of late arrivals grew from 13.4 to 20.3 between 1999 and 2009 (FAA 2012a, ASPM). The equivalent figures for Europe are 12.4 and 18.0, respectively (EUROCONTROL 2000, 2010a).

The generation of delays and their propagation throughout the system (when a flight is delayed, the next flight using the aircraft may also be delayed) have negative impacts on air transportation quality of service, on passenger's quality of travel, and, more broadly, on economic activity. Delays decrease the perceived level of service for passengers, as larger delays lower passengers' satisfaction. As for airlines, delays can result in major operational disruptions and significant costs, including costs associated with crew-scheduling disruptions, flight cancelations, and re-booking of passengers that have missed their connections (Alj 2003). Airlines may also raise air fares in order to accommodate the increase of operating costs (Miller and Clarke 2007). For the US alone, the total direct costs associated with flight delays (including costs incurred by airlines and passengers, and costs from lost demand) was about $28.9 billion in 2007. In addition to these direct costs imposed on airlines and passengers, delays are estimated to have reduced GDP by $4 billion (NEXTOR 2010).

Because the air transportation system is vital for economic activity, there is a need to find ways by which this system continues to be reliable and to meet the continued increase of demand – it is, thus, important to find solutions to airport congestion problems. Congestion at airports can be addressed through three types of approaches: *i*) the "do-nothing" alternative, *ii*) demand management mechanisms, and *iii*) scaling mechanisms (Bonnefoy and Hansman 2008). The "do-nothing" alternative is based on a self-regulatory mechanism, in which service suppliers and customers interact and adapt their behavior for the existing conditions (for instance, from the passenger standpoint, it may respond to delays at its closest airport by choosing more attractive airports in the region or by switching to other transportation modes). Demand management mechanisms attempt to address the airport congestion problems by matching demand levels and installed capacity, for instance through slot control mechanisms or congestion pricing schemes (see e.g. Le 2006). Scaling mechanisms represent a set of measures to increase the size (capacity) of components of the air transportation system, either by increasing average aircraft size (thus, increasing airport passenger throughput while using the same airport and runway resources), by changing procedures (e.g. improvement of runway efficiency and reduction of aircraft separation on approach), by spatial and temporal shifts of traffic, or by increasing the capacity of airport infrastructure.

Demand managements mechanisms are seen as short term measures, as they may constrain growth of air transportation. Ultimately, measures such as congestion pricing may prevent access of passengers from thinner markets to air transportation and airlines may be too fragile to incur any new taxes (Ferguson 2012). Improvements in efficiency and technology may accommodate increases in traffic (as foreseen by FAA in its NextGen Implementation Plan for the US, FAA 2012b), but only to some extent. In the long term, however, the increase of airport capacity, through the expansion of existing airports and the construction of new airports, may be necessary to deal with the growing volumes of traffic and attenuate the escalation of congestion problems.

2. Airport capacity decisions

The decision processes regarding the expansion of airport capacity are extremely complex (see Mozdzanowska 2008 for detailed information about the US). They involve a wide variety of stakeholders – including airport administrations, local governments, and non-governmental organizations – capable of influencing decisions to some extent, but the final choices are to be made by aviation authorities (and, ultimately, by state or federal governments). Aviation authorities (like the FAA in the US and EUROCONTROL in Europe) are responsible for regulating the air transportation system and for coordinating expansion and construction plans for the airport networks under their jurisdiction. As expansion projects compete between themselves for receiving funds, it is important to develop decision-aid tools for assisting aviation authorities at analyzing their investments in airport networks.

There are a considerable number of (academic) published studies dealing with airport expansion and/or location problems, but they focus on individual airports. Some common approaches consist in analyzing the economic impact of building or expanding one airport (see e.g. Cohen and Coughlin 2003), in comparing alternative locations for building a new airport through cost-benefit or multi-criteria analysis (see e.g. Jorge and de Rus 2004 for the former and Vreeker et al. 2002 for the latter), and in examining how proposed airport improvements affect system performance using queuing and other simulation models (Odoni et al. 1997).

Studies dealing with airport expansion and/or construction problems from the perspective of airport networks are uncommon. This is especially true for the optimization-based literature. To our best knowledge, Saatcioglu (1982) is the only study in which a set of optimization models, derived from facility location theory, are proposed to determine the optimum locations and capacities of airports within an airport network.

Some studies consider the impact of airport congestion on demand and on the traffic pattern within an airport network, but do not deal explicitly with airport expansion and/or construction problems. Hsiao and Hansen (2005) modeled passenger demand as a function of airport delay within the main airport network of U.S. and analyzed the impact of expanding Chicago O'Hare International airport. Ghobrial and Kanafani (1995) also focused on airport congestion problems within the context of an airport network, but analyzed the changes on the hubbing pattern as a consequence of congestion. Evans and Schäfer (2011) focused on a network constituted by 22 airports of the US, and analyzed three different scenarios regarding its expansion. Their approach was based on an equilibrium analysis of five profit-seeking airlines which adapted their flight frequencies, aircraft size and flight network in response to airport congestion. Ferguson (2012) used a similar approach but considering a single airline with “benevolent” behavior whose schedule is determined in order to optimize airport performance, and examined different combinations between airport operational rates and fuel prices. Ferrar (1974) and Janic (2003) are two other articles where optimization models were applied to deal with airport networks, but they focus on the utilization of existing airport capacity rather than on capacity expansion.

3. Research objectives

As stated before, there are few studies addressing airport expansion and/or construction problems at network level. Furthermore, only Saatcioglu (1982) presented a methodology, based on a set of optimization models, to determine optimum capacity improvements for airport networks under specified budget constraints. The main objective of this thesis is to develop new decision-aid tools for assisting air transportation authorities in their strategic reflections regarding the expansion of airport networks. The problem is to find the set of improvements to apply to an airport network in order to serve demand in the best possible way, for a given budget available.

The approach to be developed will rely on optimization models. It is expected that these models will require a large computation effort to be solved. Therefore, a second objective of this dissertation is to develop efficient techniques to solve the models.

The models, and corresponding solution methods, shall be validated through their application to real-world problems. Therefore, the third objective for this dissertation is to apply the models to appropriate case studies, and assess the results obtained in the light of other studies and the authors' expectations.

4. Thesis structure

This thesis is organized in seven chapters. Chapters 1 and 7 constitute, respectively, the introduction and the conclusion of the thesis. Each one of Chapters 2 to 6 presents an optimization model and/or an application of an optimization model to a case study. The chapters are interrelated and organized to form a coherent Ph.D. thesis. Despite the interrelationship between the chapters, they are to be read independently in the format of many optimization-based articles. Therefore, the chapters include; an introductory section; sections addressing model formulation and model solving issues; section(s) describing an application to a real or hypothetical problem; a final section with concluding remarks and indications for further related research. Some repetition of ideas throughout the thesis may arise due to the interdependency between the chapters.

The chapters are organized as followed:

- Chapter 2 presents the basic airport network capacity expansion model. The model applies to a set of metropolitan areas, served by airports or multi-airport systems, with known initial capacities. The purpose of the model is to determine the improvements to the airport network in order to serve future demand in the best possible way, subjected to a given budget available. The improvements to the airport network are chosen from a set of expansion actions applicable to the metropolitan areas. Each expansion action increases capacity by a discrete amount and involves a given expenditure. Expansion actions consist in improvements to the existing airports (through the reconfiguration and/or construction of runways and through improvements of terminal buildings). The objective of the model is to maximize total traffic throughput within the airport network (maximize "demand coverage"), taking into account the capacity of the airports upon travel costs and demand for air travel.

- Chapter 3 presents a heuristic method for solving the basic airport network capacity expansion model. The method is based on a bi-level scheme: the upper-level component generates tentative expansion actions to apply to the airport network, which are, in each iteration, assessed after simulating the equilibrium traffic flows and travel costs in the network in the lower-level component of the algorithm. With regard to the generation of the tentative expansion actions to apply to the airport network, seven heuristic algorithms are discussed: add and interchange (previously presented in Chapter 2 but with less detail), drop and interchange, classic variable neighborhood search, classic variable neighborhood descent, exhaustive variable neighborhood descent, classic genetic, and hybrid genetic. The algorithms are compared from the standpoint of solution quality and computational effort through their application to a large sample of randomly generated test instances.
- Chapter 4 presents a study developed for assessing the long-term capacity needs of the main airport network of the United States, which was carried out with the basic airport network capacity expansion model presented in Chapter 2. The

model is applied to the 28 metropolitan areas containing the 35 busiest airports, since these airports handle a large share of the total traffic in the US and an inadequate throughput at these airports may constrain the whole airport network. In order to capture the behavior of the regional passenger demand around the multi-airport systems, the secondary airports serving the metropolitan areas are also considered. The results obtained by the model are compared with the ones obtained by the FAA for a study conducted with the same purpose.

- Chapter 5 presents a study regarding the long-term developments of the main airport network of Germany. This study is based on an optimization model more advanced than the basic model. There are two fundamental differences between the models. First, the advanced model is applicable when some (or all) metropolitan or urban areas do not have an airport – it is a facility location model in addition to being a capacity expansion model. Second, this model explicitly considers the complementarity and competition between air travel and land travel modes such as car and train. The model is applied to the 14 metropolitan areas containing the 17 international airports. The secondary airports serving these metropolitan areas are also considered. The results obtained with the model are compared with the ones obtained by the European Center for Aviation Development.
- Chapter 6 proposes three new formulations for the airport network capacity expansion problem where the dynamic and uncertainty issues inherent to the expansion and construction of airports are addressed. The first model deals with

dynamics by looking for the best schedule to perform improvements in the airport network. The second model addresses uncertainties considering different scenarios regarding future demand. The third model considers dynamic and uncertainty issues simultaneously. The applicability of the three models is demonstrated for a small hypothetical test instance.

5. Dissemination

The research work described in the thesis was presented (and subsequently discussed) in at least one international conference, and published in the corresponding proceedings. The conferences where the research was presented are listed below.

– 1.º Workshop da Associação Portuguesa para o Desenvolvimento Regional. A expansão de redes de aeroportos: Modelo básico (Expansion of airport networks: Basic model). Lisbon, Portugal, 2008. [Chapter 2].

– 6.º Encontro do Grupo de Estudos em Transportes. A expansão de redes de aeroportos: Modelo básico (Expansion of airport networks: Basic model). Mira, Portugal, 2009. [Chapter 2]

– 13th Air Transport Research Society Conference (13th ATRS). On the optimum expansion of airport networks. Abu Dhabi, United Arab Emirates, 2009. [Chapter 2]

– 23rd European Conference on Operations Research (EURO XXIII). An optimization model for the expansion of capacity of an airport network. Bonn, Germany, 2009. [Chapters 2-3]

- 7th Triennial Symposium on Transportation Analysis (TRISTAN VII). On the optimum expansion of airport networks. Tromso, Norway, 2010. [Chapter 3]
- International Seminar on Advances in Airport, Air Traffic, and Airline Network Design. Where should airports be built or expanded?. Lisbon, Portugal, 2010. [Chapters 2-4]
- 14th Air Transport Research Society Conference (14th ATRS). The airport network of the United States – A study on long-term developments. Porto, Portugal, 2010. [Chapter 4]
- 12th World Conference on Transportation Research (12th WCTR). An optimization model for the expansion of an airport network. Lisbon, Portugal, 2010. [Chapters 2-4]
- 8.º Encontro do Grupo de Estudos em Transportes. An optimization model for the expansion of an airport network. Esmoriz, Portugal, 2011. [Chapters 2-4]
- 15.º Congresso da Associação Portuguesa de Investigação Operacional (IO 2011). An optimization model for the expansion of an airport network. Coimbra, Portugal, 2011. [Chapters 2-4]
- XXV Congresso de Pesquisa e Ensino em Transportes (XXV ANPET). Estudo sobre a evolução da rede de aeroportos dos Estados Unidos (Study on the evolution of the US airport network). Belo Horizonte, Brazil, 2011. [Chapter 4]
- 9.º Encontro do Grupo de Estudos em Transportes. Long-term developments of the German main airport network. Tomar, Portugal, 2012. [Chapter 5]

- ISOLDE XII (International Symposium on Location Decisions). Airport network capacity expansion – with a discussion of the essential ingredients of facility location. Nagoya and Kyoto, Japan, 2012. [Chapter 6]
- 1st LATSIS Symposium (European Symposium on Quantitative Methods in Transportation Systems). Long-term developments of the German main airport network: an integrated planning approach. Lausanne, Switzerland, 2012. [Chapter 5]

Further dissemination of our thesis work will be made in scientific journals. For this purpose, Chapters 2, 3, and 4 were condensed into two companion articles – respectively devoted to the basic airport network capacity expansion model ("On the Long-Term Evolution of Airport Networks: Part I - Optimization Model") and to the US main airport network study ("On the Long-Term Evolution of Airport Networks: Part II – Study for the United States") – and were submitted to the Journal of Transportation Engineering. Chapter 5 is sought as a possible contribution to the European Journal of Transport and Infrastructure Research. Chapter 6 may also be submitted to the Journal of Transportation Engineering, but before that needs to be enhanced with a practical application – which may well be the extension of the US study to a dynamic and stochastic context.

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Chapter 2

Optimization Model for Airport Network Capacity Expansion

1. Introduction

World air traffic has grown at an average annual rate of approximately 5% over the last three decades. As shown in Ishutkina and Hansman (2009), this growth in air traffic is closely correlated with the level of economic activity, and, according to ATAG (2008), strongly contributes to it – "aviation's global economic impact (direct, indirect, induced and catalytic) is estimated at USD 3,560 billion, equivalent to 7.5% of world Gross Domestic Product". In recent years, the growth pattern has changed. Between 2005 and 2009, due to the economic downturn, global air travel increased 3% in average, with the lowest rate of minus 3.5% in 2009. However, in spite of conservative assumptions concerning economic growth over the next 10-20 years, an average annual growth of 4.9% is expected (FAA 2011a).

The increase in air traffic has not been matched with an adequate expansion of infrastructure. As a consequence, the number of delayed flights has been augmenting every year. For example, in the United States (US), and despite the increase of scheduled travel times, the percentage of late arrivals grew from 13.4 to 20.3 between 1999 and 2009 (FAA 2012a, ASPM). The equivalent figures for Europe are 12.4 and 18.0, respectively (EUROCONTROL 2000, 2010a). The incidence of flight delays is especially important in some of the largest airports (over 30 percent of late arrivals at JFK, Heathrow, Newark, etc.).

Airport congestion problems can be – and are being – dealt with at various levels (aviation authorities, airports, airlines) and in several different forms (Hamzawi 1992, Forsyth 2007). In the short-term, demand management measures such as slot allocation systems and de-peaking practices can play an important role (Fan and Odoni 2002). However, in the long term, despite the efforts that are currently being made in the improvement of control systems (e.g. US's NextGEN, see FAA 2012b), a significant portion of air travel demand will be left unattended if some existing airports are not expanded and/or new airports are not built.

In this chapter, we present an optimization model for assisting aviation authorities in their strategic decisions regarding the expansion of the airport network of a country or of a community of countries willing to coordinate their investments in this type of infrastructure. The model determines in a comprehensive manner the best expansion actions to implement for each airport (or multi-airport system), while complying with a given budget. Expansion actions consist of increasing the number or changing the location of runways at existing airports, and of improving terminal buildings and apron areas. The objective is to maximize total system throughput (hence, the response to air travel demand), taking into account the capacity of airports and the impact of travel costs upon demand.

We are well aware of the fact that the decision processes regarding the expansion of airports can be extremely complex (see Mozdzanowska 2008 for detailed information about the US). They involve a wide variety of stakeholders – including airport administrations, local governments, and non-governmental organizations – capable of influencing decisions to some extent, but the final choices are to be made by aviation authorities (and, ultimately, by central governments). These choices are expected (required) by the public to be the best possible, but they are too complex to be made and discussed without appropriate decision-aid tools. The model presented in this chapter is, in our opinion, an example of such tools.

The chapter is organized as follows. We start with an overview of the literature on airport capacity expansion and related fields. Afterward, we present the optimization model developed to address airport network capacity expansion problems and describe the heuristic method used to solve it. The type of results that can be expected from the application of the model is then illustrated for a small-size, hypothetical airport network. Next, we present a study on the computational effort required to solve the model as a function of instance size. In the last section, we provide some final remarks and indicate directions for future research.

2. Literature Overview

The literature on airport capacity expansion falls into two main categories: airport expansion economics and airport site selection. The key contributions to the former subject were surveyed some years ago by Cohen and Coughlin (2003). They primarily consist of general, theoretical principles to be taken into account when making decisions on the expansion of individual airports. Very recently, Zou and Hansen (2012) extended the analysis to two airports (connected by flights of two competitive airlines). The airport site selection problems dealt with in the literature usually involve the comparison of alternative locations for building or expanding an airport in a given region. Two types of techniques are typically used for this purpose – cost-benefit analysis (see e.g. Cohen 1997, and Jorge and de Rus 2004) and multi-criteria analysis (see e.g. Paelinck 1977, Min 1994, Min et al. 1997, and Vreeker et al. 2002).

In contrast, the literature dealing with airport expansion and/or construction problems at the network level – especially the optimization-based literature – is extremely meager. The consideration of network effects is important because airports are not independent, both functionally and (often) managerially. To our best knowledge, Saatcioglu (1982) is the only article published in a leading journal where optimization models are applied to this kind of problems. Specifically, three models are proposed in that article. The first model determines the minimum number of airports necessary to cover a given demand from the population centers of a region within a given distance from the closest airport (being therefore a set covering model). The second model considers a given budget for building (or improving) an airport network, and determines the airport locations and capacities that minimize total airport construction costs and bus transportation costs for a given demand (trips to airports are assumed to be made by bus). The third model extends the previous one by considering that demand can be assigned to different types of aircraft and buses. Despite their merits, these models do not capture important features of air transportation – in particular, demand is assumed to be given instead of depending on demand-supply interactions. Ferrar (1974) and Janic (2003) are two other articles where optimization models are applied to airport networks, but they focus on the utilization of existing airport capacity (and its environmental implications) rather than on capacity expansion.

The lack of optimization-based literature on airport network capacity expansion problems is partly compensated with the abundance of literature on related, well-established subjects, particularly in the following three areas: facility location (Daskin 1995, ReVelle and Eiselt 2005), capacity expansion (Luss 1982, Van Mieghem 2003), and network design (Magnanti and Wang 1984, Yang and Bell 1998, Guihaire and Hao 2008). The work carried out within these areas with regard to hub location models (Campbell et al. 2002, Elhedhli and Hu 2005, Alumur and Kara 2008), multi-region capacity expansion models (Fong and Srinivasan 1981, Ahmed et al. 2003), location-routing models (Min et al. 1998, Albareda-Sambola et al. 2005, Nagy and Salhi 2007), and combined facility location/network design models (Melkote and Daskin 2001, Bigotte et al. 2010), certainly has linkages with the study of airport network capacity expansion problems. But it does not properly address the full set of features that characterize these problems.

3. Optimization Model

The model developed to represent the problem faced by aviation authorities when making airport network capacity expansion decisions applies to a given set of airports (or multi-airport systems), $\boldsymbol{N} = \{1, \ldots, N\}$, of known initial (declared) capacities, $s_j > 0$, $j \in \boldsymbol{N}$. We assume that airport capacities and traffic flows are both measured in enplanements (the capacity of an airport in enplanements is obtained by dividing the capacity in movements by two and multiplying the result with the average number of passengers per movement in that airport).

The set of possible expansion actions applicable to airport j is $\boldsymbol{M}_j$. The capacity increase in airport j associated with expansion action m is g_{jm}. Therefore, assuming that at most one action will be applied to an airport within the period under consideration, the future capacity of airport j, z_j, is given by:

$$z_j = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm} y_{jm}, \ \forall j \in \boldsymbol{N} \tag{1}$$

$$\sum_{m \in \boldsymbol{M}_j} y_{jm} \leq 1, \ \forall j \in \boldsymbol{N} \tag{2}$$

where y_{jm} is a binary variable that is equal to one if action m is applied to airport j and is equal to zero otherwise.

The expenditure associated with the application of action m to airport j is e_{jm}. The total expenditure must comply with the budget available for expansion actions, b. Therefore,

$$\sum_{j \in \boldsymbol{N}} \sum_{m \in \boldsymbol{M}_j} e_{jm} \, y_{jm} \leq b \tag{3}$$

The (future) capacity of airport j must be able to accommodate the traffic flow in the airport, w_j. That is,

$$z_j \geq w_j, \ \forall j \in \boldsymbol{N} \tag{4}$$

The traffic flow in airport j is obtained by adding the flows u_l for each flight leg l with endpoint at airport j, which, in turn, are obtained by adding the flows v_{jkr} on each possible flight route r between airports j and k where flight leg l is included. That is,

$$w_j = \sum_{l \in \boldsymbol{L}_j} u_l, \forall j \in \boldsymbol{N} \tag{5}$$

$$u_l = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{r \in \boldsymbol{R}_l} v_{jkr}, \forall l \in \boldsymbol{L} \tag{6}$$

where $\boldsymbol{L}_j$ is the set of flight legs with endpoint at airport j and $\boldsymbol{R}_l$ is the set of flight routes that include flight leg l.

The traffic flow on each route r connecting airports j and k is assumed to be related with the (O/D) traffic flow between these airports, q_{jk}, and the travel costs incurred by the passengers for each route, c_{jkr}, according to a logit model. This is the type of model typically used for describing route choice in air traffic simulation models (see e.g. Ghobrial and Kanafani 1995 and Hsiao and Hansen 2005, where, respectively a multinomial logit model and a nested logit model are used). The logit model we consider is as follows:

$$v_{jkr} = \frac{e^{-\gamma c_{jkr}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkp}}} q_{jk}, \ \forall j,k \in \boldsymbol{N}, r \in \boldsymbol{R}_{jk} \tag{7}$$

where $\boldsymbol{R}_{jk}$ is the set of routes connecting airports j and k, and γ is a calibration parameter.

The (O/D) traffic flow between airports j and k is assumed to be described by a demand function having as arguments the size (mass) of the centers (regions) served by the airports, p_j and p_k (which depend on factors such as population, income per capita, and tourism activity level), the average air travel cost between the airports, c_{jk}, and a factor reflecting the competition from other modes connecting the centers where the airports are located. These are variables typically included in air travel demand functions (see e.g. Jorge-Caldéron 1997). The demand function considered can be represented as follows:

$$q_{jk} = Q(p_j, p_k, \phi_{jk}, c_{jk}), \ \forall j,k \in \boldsymbol{N} \tag{8}$$

where ϕ_{jk} is the modal split factor.

The average air travel cost between airports j and k is given by:

$$c_{jk} = \frac{\sum_{r \in \boldsymbol{R}_{jk}} c_{jkr} v_{jkr}}{q_{jk}}, \ \forall j,k \in \boldsymbol{N} \tag{9}$$

The air travel costs incurred by passengers consist of ticket fares and time costs. Ticket fares are assumed to reflect the flight and airport costs (fuel, crew, aircraft depreciation and maintenance, landing fees, check-in, luggage handling, etc.) of efficient airlines. This assumption is consistent with the idea that, in the long term, under airspace liberalization policies, inefficient airlines will be eliminated and efficient airlines will keep increasing the flights they offer until ("unfair") profits are cancelled out. Flight costs are assumed to increase with travel distance and, because of economies of scale, to decrease with traffic flow (Hsiao and Hansen 2005). Airport costs are assumed to increase with the utilization rate at airports above a given level of this rate, because congestion will make airport operations more expensive (de Neufville and Odoni 2003), and to include a possible congestion tax levied by the aviation authority to regulate the utilization of airports (in their absence, excess demand situations could occur and airports would be able to take advantage of their local monopolistic position for making "unfair" profits). The time cost of a trip is the value of the time spent on the flight (or flights) included in that trip and at airports (origin, destination, and possible hubs). The time spent on flights is assumed to be proportional to travel distance. The time spent on airports is assumed to increase with the airport utilization rates, because of congestion delays (and to have a fixed component corresponding to check-in, security procedures, luggage retrieval, etc.). Hence, air travel costs can be expressed as follows:

$$c_{jkr} = \sum_{l \in \boldsymbol{L}_{jkr}} C_1\left(d_l, u_l\right) + \sum_{n \in \boldsymbol{N}_{jkr}} \left[C_2\left(\frac{w_n}{z_n}\right) + x_n \right], \ \forall j,k \in \boldsymbol{N}, r \in \boldsymbol{R}_{jk} \tag{10}$$

with

$$\partial C_1 / \partial d_l > 0, \; \partial C_1 / \partial u_l < 0, \text{ and } dC_2 / d\frac{w_n}{z_n} > 0$$

where d_l is the length of flight leg l, w_n/z_n is the utilization rate at airport n, x_n is the congestion tax for airport n, $\boldsymbol{L}_{jkr}$, is the set of legs included in route r, and $\boldsymbol{N}_{jkr}$ is the set of airports included in route r.

The objective is to maximize total system throughput as measured by the total number of trips made within the airport network. That is,

$$\max Q = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jk} \tag{11}$$

This objective was chosen because it is in line with the demand coverage objective often adopted in public facility planning and can be easily accepted by stakeholders. A possible alternative, of the same nature, would be to measure system throughput in terms of revenue passenger kilometers/miles. Another possible alternative, of a different nature, would be to maximize social welfare. Such objective would certainly be more meaningful from the economic point of view. However, because it corresponds to a more complex concept, model results would be more difficult to discuss.

Expressions (1)-(11) define the optimization model developed to represent the airport network capacity expansion problems faced by aviation authorities. It is a complex mixed-integer nonlinear optimization model relying on a relatively simple description of an air transportation system, but which we believe captures the essential facets of such system that need to be taken into account when making strategic decisions with respect to the evolution of an airport network.

4. Solution Method

The complex model presented in the previous section is extremely difficult (if not impossible) to solve to exact optimality even for moderate-size instances. Thus, a heuristic method was developed to solve the model. This method comprises two iterative procedures: (1) determination of capacity expansion actions; (2) determination of equilibrium flows and travel prices/costs. The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the airports consistent with the budget available, and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The second procedure (lower-level) procedure determines the equilibrium traffic flows and costs for each tentative expansion action. It also determines the congestion taxes to apply in order to cancel out excess demand situations that might occur in some airport(s).

The solution method is outlined in Figure 1. The upper-level procedure starts by setting the initial airport capacities at their current values, that is, $z_j = s_j$ (for all j in $\boldsymbol{N}$), and the congestion taxes at zero. Then, in successive iterations, it calls the lower-level procedure, which starts by setting the traffic flows at zero. Next, the travel cost for each itinerary r connecting O-D pair j-k (for all j and k in $\boldsymbol{N}$ and for all r in $\boldsymbol{R}_{jk}$), c_{jkr}, is calculated using expression (10). With the average travel cost for each O-D pair j-k, c_{jk}, the traffic between j and k, q_{jk}, is calculated through expression (8). The traffic between j and k is then assigned to each route r in $\boldsymbol{R}_{jk}$ through expression (7). After assigning traffic to routes, the leg and airport flows are calculated using expressions (5) and (6), respectively. Until convergence (that is, until the flows on the legs are the same in consecutive iterations, except for a small tolerance), the travel costs are updated according to the flows on the legs and the utilization rate of airports, and the traffic flows are updated as a function of the current travel costs. The equilibrium flows (and costs) are obtained using the successive averages method (Robbins and Monro 1951, Powell and Sheffi 1982, Ortúzar and Willumsen 2011 p. 370). It is important to emphasize here that, though we were not able to demonstrate analytically that equilibrium flows are unique, we always found the same equilibrium flows in empirical tests carried out for numerous random instances (generated as described in the following section) with different random initial flows. After computing the equilibrium flows, if the capacities of some airports are exceeded (i.e., if expression 4 is violated for some airports), congestion taxes are successively applied to the airport with the smallest positive excess demand, until a solution where airports are not affected by excess demand is found. At this point, the lower-level procedure calls back the upper-level procedure, which computes the value of the solution found (with respect to total system throughput), Q, and compares it with the value of the current best solution, Q^*. If the solution is better than the current best solution ($Q > Q^*$), it is set as the current best solution, and expansion actions complying with the available budget are generated according with a greedy algorithm (alternatively, any other local, population, or model-based search algorithm could be used). The expansion actions change the capacities of airports according to expression (1), and with the new capacities the two procedures are repeated until the current best solution ceases to improve.

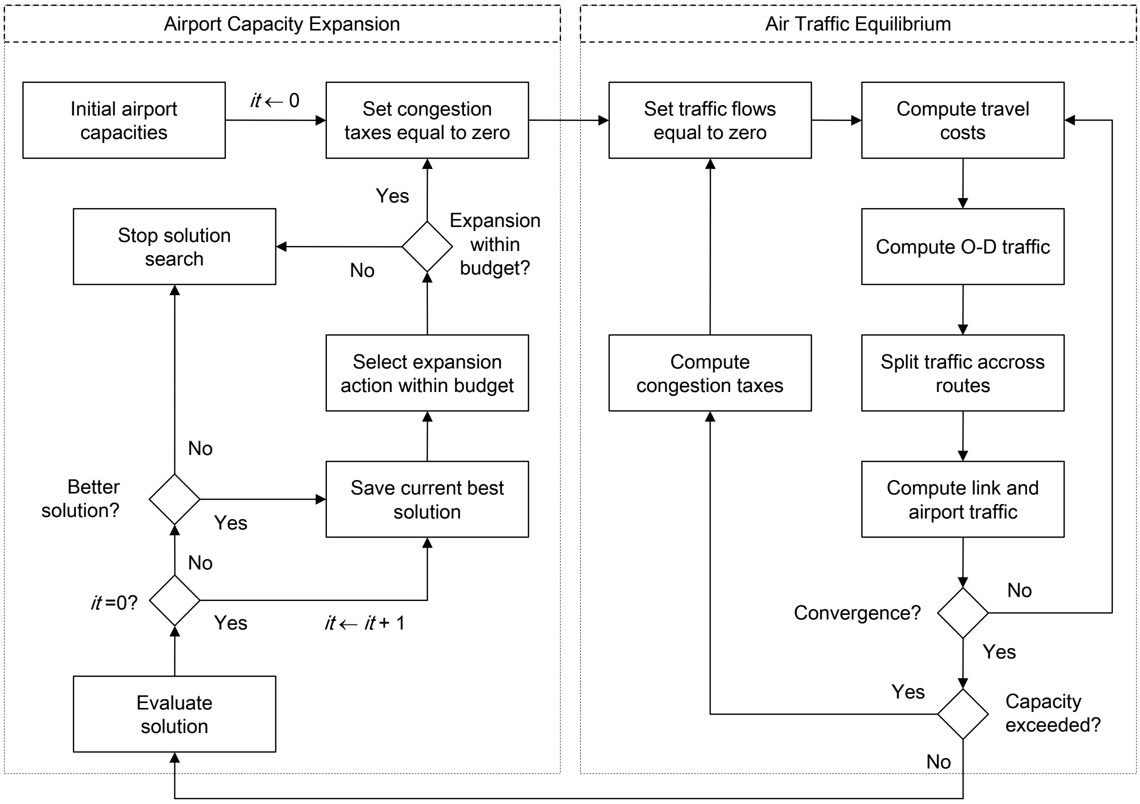

Figure 1 – Algorithm Outline

5. Application Example

The type of results that can be obtained through the application of the optimization model presented in Section 3 will be illustrated for Instance #1 of a set of random instances generated for a region with six population centers, each one served by one airport. The application consists in analyzing the implications for the airport network of a 25 percent increase of the size of all population centers and in determining the expansion actions to implement in response to the population increase as a function of the budget available.

Below we provide detailed information on the data used to run the model and on the results obtained through its application.

5.1 Data

The population centers are randomly distributed over a square-shaped region with 4,000 × 4,000 km^2 (Table 1). The sizes (populations) of the population centers were randomly determined to follow Zipf's rank-size rule considering the maximum population of 20 million for the largest center (Beckmann 1958, Brakman et al. 1999). According to this rule, the population of the largest center is *n* times the population of the *n*-largest center (apart from a random perturbation).

Table 1 – Coordinates and population of centers

Center	Coordinates (km)		Population
	X	Y	(10^6 inhabitants)
1	369	3026	17.162
2	3722	1535	7.180
3	2685	1534	4.474
4	3539	2078	3.295
5	952	1051	2.658
6	3014	3637	1.948

All centers are served by an airport. Airports can have six possible layouts. The possible layouts and corresponding airport capacities are listed in Table 2.

Table 2 – Possible airport layouts and capacities

Layout	Runway configuration	Capacity (10^3 pax/day)
1	Single runway	40
2	Two close parallel runways	60
3	Two medium spaced parallel runways	70
4	Two independent parallel runways	80
5	Three runways (two close runways plus one)	100
6	Four runways (two pairs of close parallel runways)	120

The demand function, the modal split factor, the route choice (logit) model, and the cost functions (C_1 and C_2) are as follows:

$$q_{jk} = 1.8\, p_j\, p_k\, \phi_{jk}\, c_{jk}^{-0.5},\ \forall j,k \in \boldsymbol{N} \tag{12}$$

$$v_{jkr} = \frac{e^{-0.03 c_{jkr}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-0.03 c_{jkp}}}\, q_{jk},\ \forall j,k \in \boldsymbol{N}, r \in \boldsymbol{R}_{jk} \tag{13}$$

$$\phi_{jk} = \begin{cases} 0 \Leftarrow l_{jk} \le l_{jk\min} \\ \dfrac{l_{jk} - l_{jk\min}}{l_{jk\max} - l_{jk\min}} \Leftarrow\le l_{jk\min} < l_{jk} < l_{jk\max} \\ 1 \Leftarrow l_{jk} \ge l_{jk\max} \end{cases},\ \forall j,k \in \boldsymbol{N} \tag{14}$$

where l_{jk} is the (Euclidean) distance between centers j and k, $l_{jk_{\min}}$ = 200 km (distance below which all traffic is by land) and $l_{jk_{\max}}$ = 1000 km (distance above which all traffic is by air).

$$C_1(d_l, u_l) = \begin{cases} \left(1 - \dfrac{0.5}{20} \times u_l\right) \times 0.06 \times d_l \Leftarrow u_l < 20 \\ 0.03 \times d_l \Leftarrow u_l \ge 20 \end{cases},\ \forall l \in \boldsymbol{L} \tag{15}$$

$$C_2\left(w_n/z_n\right)=\begin{cases}20 \Leftarrow w_n/z_n \leq 0.8 \\ 100\times w_n/z_n - 60 \Leftarrow w_n/z_n > 0.8\end{cases}, \quad \forall n \in \boldsymbol{N} \qquad (16)$$

The units for the variables included in these expressions are: q_{jk}, v_{jkr}, u_l, w_n, and z_n, 10^3 pax/day; p_j, million inhabitants; c, C_1, and C_2, \$/pax; and l_{jk} and d_l, km.

The existing airport network is described in Figure 2 and Table 3. All airports are single runway airports (Layout 1). The airports of the two largest centers (Centers 1 and 2) are hub airports, and other airports are non-hub airports, serving only as trip origins or destinations. The two hub airports are somewhat congested (the utilization rate exceeds 80% in both cases). The total system throughput is 100.9×10^3 pax/day. The route flows are shown in Table 4 (and the corresponding leg flows in Table 5). All centers are connected with non-stop flights with the exception of Centers 5 and 6 which do not generate traffic enough for this to happen (we assumed that a flight leg would only exist for a traffic flow of at least 500 pax/day). As could be expected, the most important market is Market 1-2, corresponding to trips between Center 1 and Center 2, with 13.1×10^3 pax/day (each way), all non-stop. This is 73.6% of the 17.8×10^3 pax/day that fly Leg 1-2. The remaining 26.4% are trips that use Airport 1 or Airport 2 as a hub. Trips are made predominantly (≈87%) through non-stop flights. However, for some markets, the fraction of trips made through connecting flights is high. This is, naturally, the case of Market 5-6 (since it is not served by non-stop connections), and also the case of Market 1-4, for which 40.7% of trips are made through Airport 2 (2.2 out of 5.4×10^3 pax/day). In the latter case, the reason for such a large fraction of non-stop trips is because flight costs are much lower for Leg 1-2 than for Leg 1-4 due to the traffic being much higher, compensating for the additional airport costs of a stop in Airport 2.

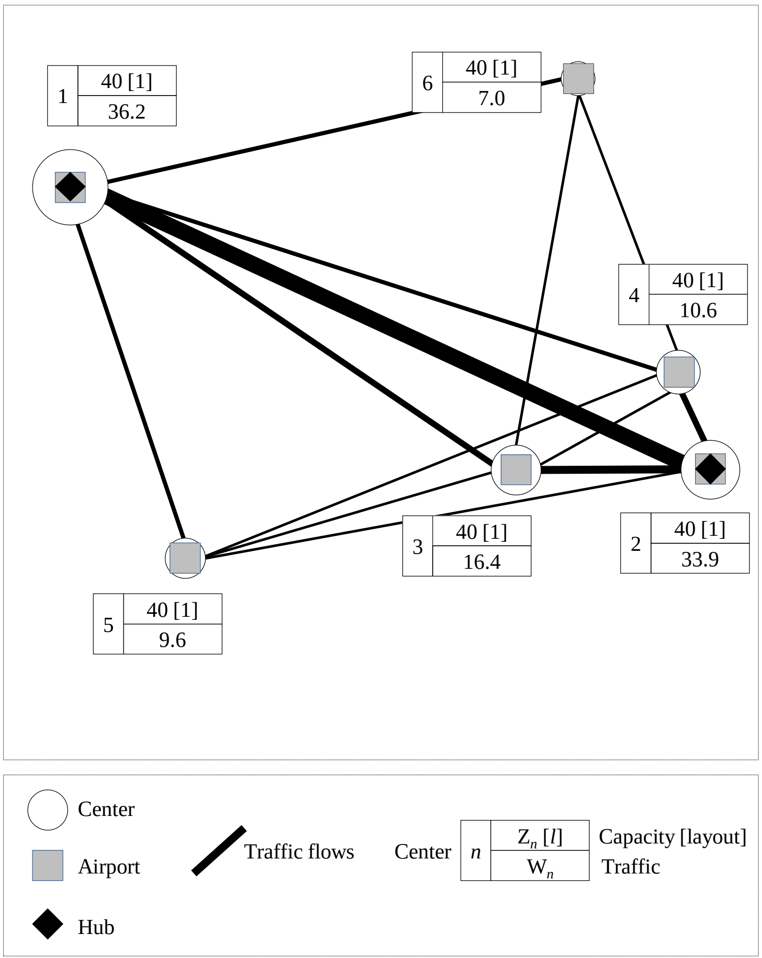

Figure 2 – Existing airport network

Table 3 – Airport information for the existing airport network

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	40	36.2	91	30.6	0.0
2	40	33.9	85	24.8	0.0
3	40	16.4	41	20.0	0.0
4	40	10.6	26	20.0	0.0
5	40	9.6	24	20.0	0.0
6	40	7.0	17	20.0	0.0

Table 4 – Route flows in the existing airport network

Airport		Traffic (10^3 pax/day)		
Origin	Destination	Non-stop	Through Airport 1	Through Airport 2
1	2	13.1	-	-
1	3	6.2	-	1.7
1	4	3.2	-	2.2
1	5	4.9	-	0.2
1	6	3.0	-	0.3
2	3	4.3	0.1	-
2	4	1.6	0.0	-
2	5	1.7	0.2	-
2	6	1.5	0.1	-
3	4	1.4	0.0	0.5
3	5	1.2	0.1	0.1
3	6	0.7	0.0	0.2
4	5	0.6	0.0	0.2
4	6	0.6	0.0	0.1
5	6	0.0	0.2	0.2

Table 5 – Leg flows in the existing airport network

Traffic (10^3 pax/day)						
Origin	Destination airport					
airport	1	2	3	4	5	6
1	0.0	17.8	6.3	3.2	5.5	3.4
2	17.8	0.0	6.7	4.7	2.4	2.3
3	6.3	6.7	0.0	1.4	1.2	0.7
4	3.2	4.7	1.4	0.0	0.6	0.6
5	5.5	2.4	1.2	0.6	0.0	0.0
6	3.4	2.3	0.7	0.6	0.0	0.0

The expenditure involved in the expansion of airports is presented in Table 6.

Table 6 – Airport expansion costs (x10^8\$)

Cost (10^8 \$)						
Initial airport	Final airport layout					
layout	1	2	3	4	5	6
No airport	8	10	12	14	16	18
1	-	6	8	9	12	14
2	-	-	5	6	9	11
3	-	-	-	4	7	9
4	-	-	-	-	6	8
5	-	-	-	-	-	5

5.2 Results

As stated before, the application consists in determining the expansion actions to implement in response to a 25% increase of the size of all population centers as a function of the budget available for the improvement of the existing airport network.

According with the outcomes of the optimization model, if nothing is done (budget b = 0), the hub airports will become severely congested (Figure 3 and Table 7). The level of congestion will be especially important in Airport 1, where it will be necessary to apply a congestion tax of 92.10$ to regulate the utilization of the airport (avoiding excess demand situations). The total system throughput will rise to 127.9×10^3 (+26.7%). The percentage of non-stop trips will also rise, though less clearly, from approximately 87 to 92%, in part because congestion in the hub airports will divert traffic to non-stop flights. Indeed, there will be no trips made through Airport 1 and the number of trips made through Airport 2 will be smaller except for Route 4-2-6 (Table 8). Another reason for the increase of non-stop trips is because, due to population increase, Centers 5 and 6 will generate traffic enough to justify non-stop flight connections.

The less expensive way of completely eliminating (future) congestion consists in upgrading the layouts of Airports 1 and 2 to Layout 4, that is, “two independent parallel runways” (Figure 4 and Table 9). The capacity of both airports would therefore increase from 40 to 80×10^3 pax/day. Since the expenditure involved in updating a single runway airport to an airport with two independent parallel runways is 9×10^8\$, a budget of 18×10^8\$ would have to be allocated to airport expansion actions. After the implementation of these actions, the total system throughput would grow to 167.8×10^3 pax/day (+66.3%), with the percentage of non-stop trips decreasing from 87 to 85% because the elimination of congestion at hub airports favors connecting flights (Table 10).

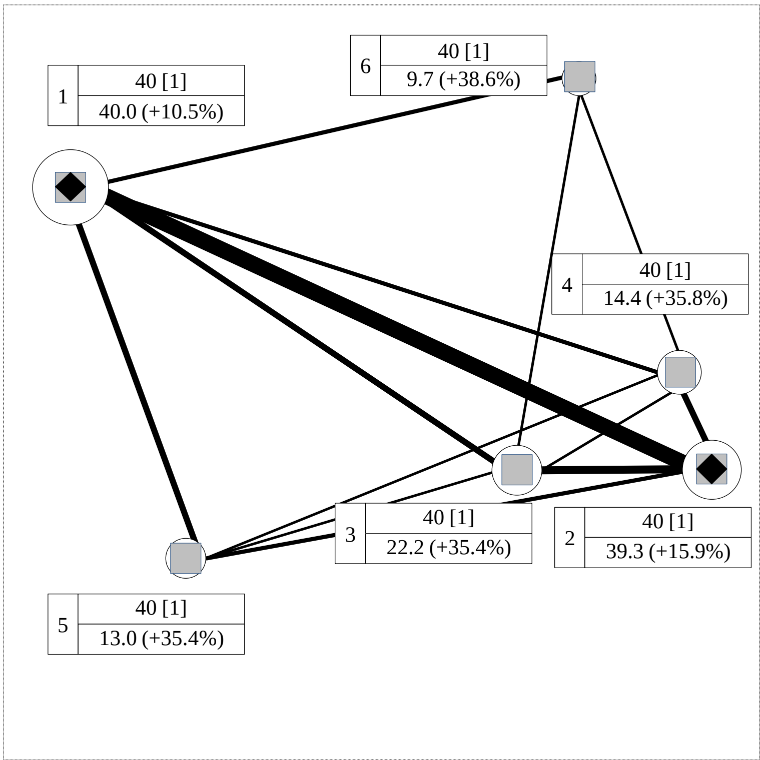

Figure 3 – Optimum airport network for *b*=0

Table 7 – Airport information for the optimum airport network with *b*=0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	40	40.0	100	40.0	92.1
2	40	39.3	98	38.2	0.0
3	40	22.2	56	20.0	0.0
4	40	14.4	36	20.0	0.0
5	40	13.0	32	20.0	0.0
6	40	9.7	24	20.0	0.0

Table 8 – Route flows in the optimum airport network for *b*=0

Airport		Traffic (10^3 pax/day)		
Origin	Destination	Non-stop	Through Airport 1	Through Airport 2
1	2	14.6	-	-
1	3	7.8	-	1.4
1	4	4.4	-	2.1
1	5	5.6	-	0.1
1	6	3.7	-	0.3
2	3	6.4	0.0	-
2	4	2.4	0.0	-
2	5	2.9	0.0	-
2	6	2.3	0.0	-
3	4	2.4	0.0	0.6
3	5	2.0	0.0	0.2
3	6	1.3	0.0	0.2
4	5	1.1	0.0	0.3
4	6	1.0	0.0	0.2
5	6	0.7	0.0	0.1

If only 9×10^8\$ could be made available for airport expansion actions (half of the budget needed to fully eliminate congestion in the airport network), the best option would be to improve Airport 1 from Layout 1 to Layout 4, and leave Airport 2 unchanged and affected by severe congestion despite the application of a congestion tax of 15.82\$ (Figure 5 and Table 11). The total system throughput would reach 156.8×10^3 pax/day (+55.3%). This means that approximately 70% of the possible system throughput gains can be made with only 50% of the budget needed to completely eliminate congestion in the airport network. The percentage of non-stop flights would grow to 93%, because the increase in connecting flights through Airport 1 would not be enough to compensate for the decrease of connecting flights through Airport 2 (Table 12).

The impact of increasing the budget on total system throughput is summarized in Figure 6 and Table 13. They show that the minimum budget necessary for improving the airport network is 6×10^8\$. The best way of applying this amount would be in the upgrade of Airport 1 from Layout 1 to Layout 2 ("two close parallel runways"), and would have a great impact on total system throughput. Additional amounts up to 11×10^8\$ should also be applied in Airport 1. Above that amount, the budget should be distributed by Airports 1 and 2, either equally or in favor of Airport 1.

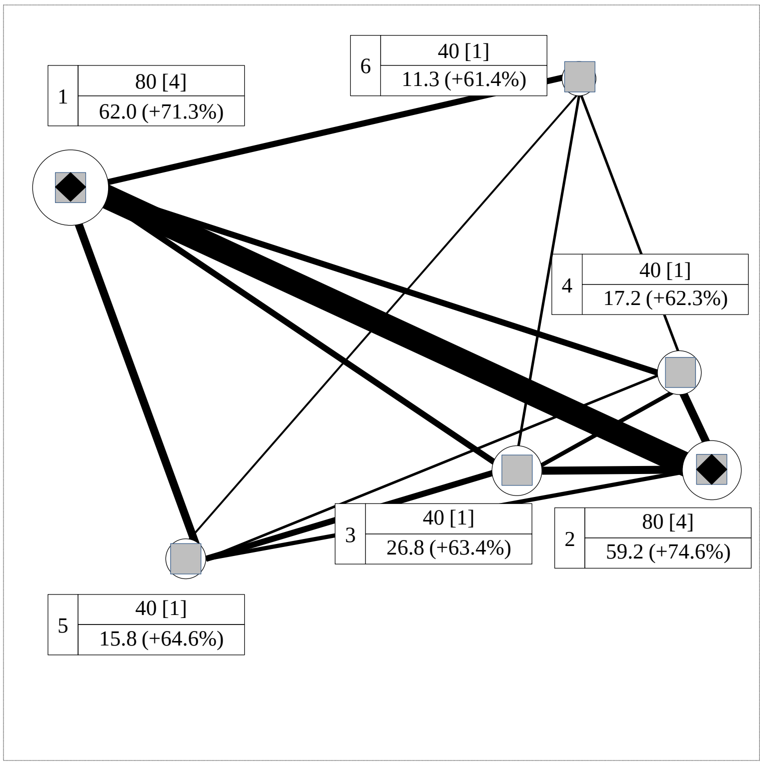

Figure 4 – Optimum airport network for *b*=18x10^8 \$

Table 9 – Airport information for the optimum airport network with *b*=18x10^8\$

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	80	62.0	77	20.0	0.0
2	80	59.2	74	20.0	0.0
3	40	26.8	67	20.0	0.0
4	40	17.2	43	20.0	0.0
5	40	15.8	39	20.0	0.0
6	40	11.3	28	20.0	0.0

Table 10 – Route flows in the optimum airport network for *b*=18x10^8\$

Airport		Traffic (10^3 pax/day)		
Origin	Destination	Non-stop	Through Airport 1	Through Airport 2
1	2	22.6	-	-
1	3	9.9	-	3.3
1	4	4.7	-	4.3
1	5	8.2	-	0.4
1	6	4.9	-	0.7
2	3	6.9	0.2	-
2	4	2.6	0.0	-
2	5	2.5	0.6	-
2	6	2.3	0.2	-
3	4	2.1	0.0	0.9
3	5	1.7	0.2	0.2
3	6	1.1	0.1	0.3
4	5	0.9	0.1	0.4
4	6	0.9	0.0	0.2
5	6	0.5	0.2	0.1

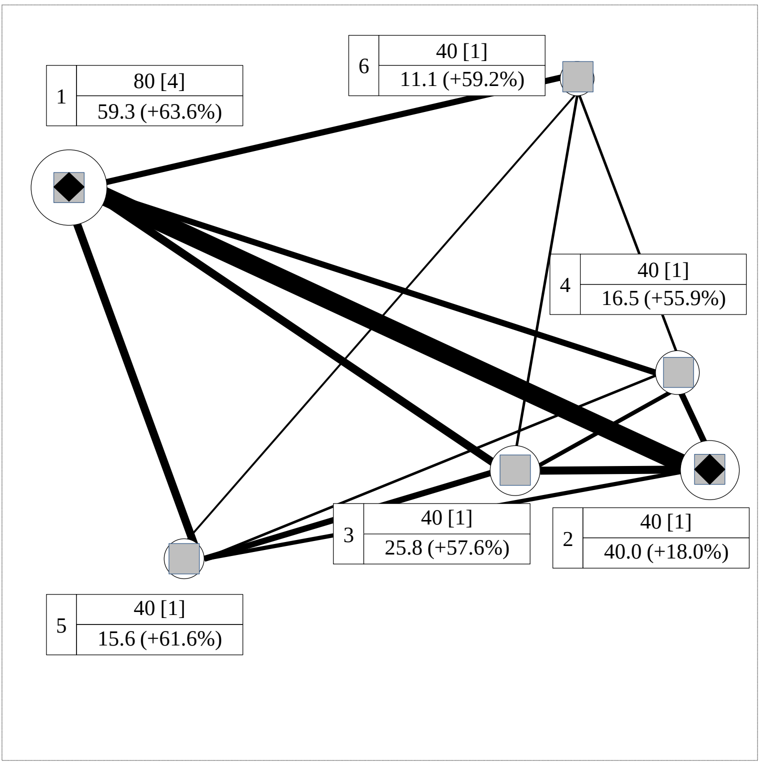

Figure 5 – Optimum airport network for *b*=9x10^8 \$

Table 11 – Airport information for the optimum airport network with b=9x10^8\$

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	80	59.3	74%	20.0	0.0
2	40	40.0	100%	40.0	15.8
3	40	25.8	64%	20.0	0.0
4	40	16.5	41%	20.0	0.0
5	40	15.6	39%	20.0	0.0
6	40	11.1	28%	20.0	0.0

Table 12 – Route flows in the optimum airport network for b=9x10^8 \$

Airport		Traffic (10^3 pax/day)		
Origin	Destination	Non-stop	Through Airport 1	Through Airport 2
1	2	19.3	-	-
1	3	12.4	-	1.1
1	4	7.1	-	1.8
1	5	8.5	-	0.1
1	6	5.4	-	0.2
2	3	5.5	0.2	-
2	4	2.1	0.0	-
2	5	2.2	0.6	-
2	6	2.0	0.2	-
3	4	2.6	0.1	0.4
3	5	1.8	0.2	0.1
3	6	1.3	0.1	0.1
4	5	1.1	0.1	0.1
4	6	1.1	0.0	0.1
5	6	0.6	0.2	0.0

6. Computational Study

In this section we present a study on the computational effort required to solve the model for a set of 20 random instances of 10, 20, and 40 airports, of which 20% or 40% are hub airports, using two types of greedy algorithms in the upper-level (capacity expansion) procedure of the solution method: a Add+Interchage algorithm (AIA) and a Drop+Interchange algorithm (DIA). In the AIA, the airports are set initially at their current capacities; then, in successive iterations, the airport one-level capacity expansion that most improves total system throughput is chosen until no more throughput improvements are possible within the available budget; finally, one-level capacity expansions are shifted between airports, once again until no more throughput improvements are possible. The DIA is essentially the opposite, starting with the airports at their maximum possible capacities.

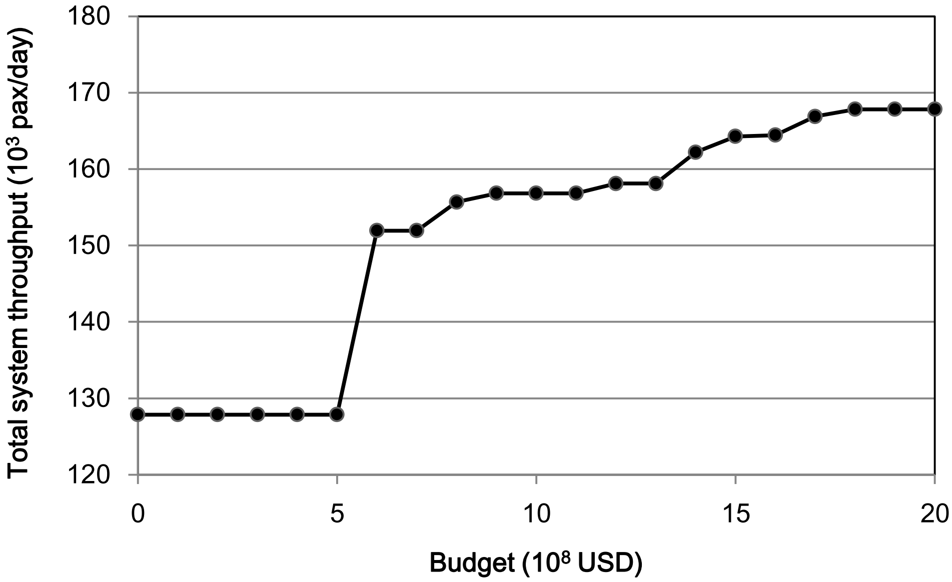

Figure 6 – Total system throughput as a function of budget

Table 13 – Optimum layout of Airports 1 and 2 as a function of budget

Budget	Layout	
(10^8 \$)	Airport 1	Airport 2
0	1	1
6	2	1
8	3	1
9	4	1
11	4	1
12	2	2
14	3	2
15	4	2
16	3	3
17	4	3
18	4	4

The results we have obtained are summarized in Table 14 and Table 15, respectively for a situation with no budget constraints and for a situation with half of the budget required to fully eliminate congestion problems. The experiments were carried out on a 2.83 GHZ Intel Core 2 Quad Q9550 computer with 4 GB of RAM.

Table 14 – Results with no budget constraints

Instance size	Solution method	Percentage of hub airports: 20			40		
		CPU (secs)	Best solutions (%)	Max. deviation (%)	CPU (secs)	Best solutions (%)	Max. deviation (%)
10	AIA	0.0	100.0	0.0	7.0	100.0	0.0
	DIA	0.0	100.0	0.0	0.6	100.0	0.0
20	AIA	0.0	95.0	0.0	283.9	95.0	0.0
	DIA	0.0	100.0	0.0	20.4	95.0	0.0
40	AIA	0.0	40.0	2.3	21654.4	100.0	0.0
	DIA	0.0	80.0	0.9	13612.7	25.0	0.3

Table 15 – Results with budget constraints

Instance size	Solution method	Percentage of hub airports: 20			40		
		CPU (secs)	Best solutions (%)	Max. deviation (%)	CPU (secs)	Best solutions (%)	Max. deviation (%)
10	AIA	1.1	100.0	0.0	6.4	85.0	1.1
	DIA	2.1	85.0	6.5	5.3	70.0	2.7
20	AIA	72.5	75.0	1.6	131.5	80.0	4.1
	DIA	133.2	65.0	2.3	245.5	65.0	5.6
40	AIA	8947.9	20.0	1.7	5309.2	100.0	0.0
	DIA	6371.0	80.0	0.7	4322.4	25.0	0.9

The analysis of the tables reveals that computational effort increases sharply with instance size. For example, the average time required to solve 10-airport instances with the AIA is less than 3 seconds. The equivalent figures for 20- and 40-airport instances are around 150 and 18,050 seconds. The computational effort does not necessarily increase with the number of hubs considered, despite the fact that more hubs signify more routes to compute. The DIA generally provides the best solutions when there are no budget constraints, taking always less time to finish the search. The AIA generally provides the best solutions when there are budget constraints, taking less time to finish the search in most of the instances with 10 and 20 airports. For 40-airport instances, the DIA becomes faster and provides solutions with good quality (maximum deviation of 1.68% for the solutions provided by the AIA).

The 10-airport instances were solved by complete enumeration for the situation with budget constraints. The solutions we obtained for 20% hub airports were the same as the ones obtained through the AIA, which means that this algorithm always found a (global) optimum solution. The DIA provided the optimum solution for 17 instances (for one of the remaining 3 the solution was 6.49% worse than the optimum). For 40% hub airports, the quality of the solutions provided by both algorithms was worse, but the AIA performed better, delivering the optimum solution in 16 instances (maximum deviation to the optimum solution value of 1.43%), whereas the DIA found the optimum solution in 14 instances (maximum deviation of 2.81%).

7. Conclusion

In this chapter we presented an optimization model for assisting aviation authorities in the determination of the best expansion actions to implement in an airport network, while complying with a given budget. The model maximizes total system's throughput, taking into account the capacity of the airports and the impact of travel costs upon demand. As illustrated for a small-size, hypothetical network, the model can be of great practical utility.

For solving the model, we developed a heuristic method consisting of two iterative procedures: (1) determination of capacity expansion actions; (2) determination of equilibrium flows and travel prices/costs. This method was tested using, alternatively, an Add+Interchage algorithm and a Drop+Interchage procedure. In general, the former method performed better when there were budget constraints to take into account, and the latter in the absence of such constraints. Both algorithms, especially Add+Interchage, took a considerable amount of time to handle 40-airport instances. This means that large real-world airport networks will be difficult to handle through the model.

In the near future, our main efforts will certainly be directed towards the enhancement of the heuristic method, and in particular to test other types of algorithms for its capacity expansion procedure. But we also want to augment the model with a number of new, important features. In particular, we plan to consider the construction of new airports in addition to the expansion of the existing ones. Also, we plan to address three types of issues that aviation authorities have to care about: equity issues; robustness issues; and flexibility issues. Indeed, the solutions to airport network capacity expansion problems must consider the needs of regions located far away from heavily populated areas (equity), must perform well enough even under adverse conditions (robustness), and must be capable of incorporating changes as new information becomes available (flexibility). An optimization model with all these features that could be solved within reasonable computation effort would certainly be a very important tool for assisting air transportation authorities at making the best decisions with regard to the expansion of airport networks.

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Chapter 3

Solving the Airport Network Capacity Expansion Model

1. Introduction

The air transportation industry has assumed an important role for the mobility of people and goods and for economic activity worldwide (Ishutkina and Hansman 2009). As of 2000, it was responsible for the transportation of about 1.7 billion passengers and large amounts of cargo, and generated revenues on the order of US $1 trillion (de Neufville and Odoni 2003).

Demand for air transportation has been continuously growing over the past three decades, propelled by a generalized increase of population and purchasing power, international business and trade, and also by technological improvements (Nanayakkara 2008). The growth in traffic has not been matched by an adequate increase of infrastructure capacity, particularly of the airport resources, and this has led to the escalation of congestion problems at several airports worldwide. In order to deal with the growing volumes of air traffic and attenuate the escalation of congestion problems, there is the need to scale the capacity of the airport infrastructures in order to cope with future demand, both through the expansion of the existing airports and/or the construction of new airports.

In Chapter 2 we presented an optimization model for assisting aviation authorities in their strategic decisions regarding the expansion of airport networks. The model determines in a comprehensive manner the best expansion actions to implement for each airport (or multi-airport system), while complying with a given budget. Expansion actions consist of increasing the number or changing the location of runways at existing airports, and of improving terminal buildings and apron areas. The objective is to maximize total system throughput, taking into account the capacity of the airports and the impact of travel costs upon demand.

The model presented is a nonlinear mixed integer optimization model, which is difficult to solve using exact solution methods. Therefore, a heuristic solution approach was proposed to solve the model. The approach comprises two iterative procedures: (1) determination of capacity expansion actions; and (2) determination of equilibrium flows and travel costs. The upper-level procedure establishes and evaluates, in each iteration, candidate expansion actions for the airports, and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The lower-level procedure determines the equilibrium traffic flows and costs for each tentative expansion action. In this chapter, we propose some improvements to the solution method, with focus on the generation of the candidate expansion actions (upper-level procedure). Three families of algorithms were considered: local search algorithms, variable neighborhood search algorithms, and genetic algorithms.

This chapter is organized as follows. In Section 2, we explain in detail the solution approach for solving the model, and describe the algorithms developed to generate the candidate expansion actions. In Section 3, we compare the performance of the algorithms from the standpoint of solution quality and computation effort through their application to a large sample of randomly generated networks with different sizes. In Section 4, we provide some final remarks.

2. Solution method

The complex optimization model presented in Chapter 2 is extremely difficult (if not impossible) to solve to exact optimality even for moderate-size instances. Thus, a heuristic method was developed to solve the model. This method comprises two procedures, corresponding, respectively, to the determination of capacity expansion actions and to the determination of equilibrium flows and travel costs (Figure 7). The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the airports (candidate solutions), and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The second (lower-level) procedure determines the equilibrium traffic flows and costs for each tentative expansion action. It also determines the congestion taxes to apply in order to eliminate the excess demand situations that might occur in some airport(s). The two procedures are executed iteratively until system throughput ceases to increase. Detailed information about both procedures is provided below in separate subsections.

2.1 Airport capacity expansion

The airport capacity expansion procedure can be implemented considering various types of algorithms. Specifically, we have considered three types of algorithms that have been often applied to facility location and capacity expansion models: classic local search algorithms (Kuehn and Hamburger 1963, Teitz and Bart 1968, Arya et al. 2004); variable neighborhood search algorithms (Hansen and Mladenović 1997, 2001, Ilić et al. 2010); and genetic algorithms (Gong et al. 1997, Kratica et al. 2001, Bozkaya et al. 2002, Jaramillo et al. 2002, Correa et al. 2004).

2.1.1 Classic local search algorithms

Local search algorithms evolve from a given initial solution by successively selecting the local change (or move) which leads to the best improvement of the objective function (see e.g. Michalewicz and Fogel 2004). Different schemes of local search algorithms may arise depending on the neighborhood structure(s) considered when generating local moves. Two local search algorithms were developed for this application: Add+Interchange algorithm (AIA) and Drop+Interchange algorithm (DIA).

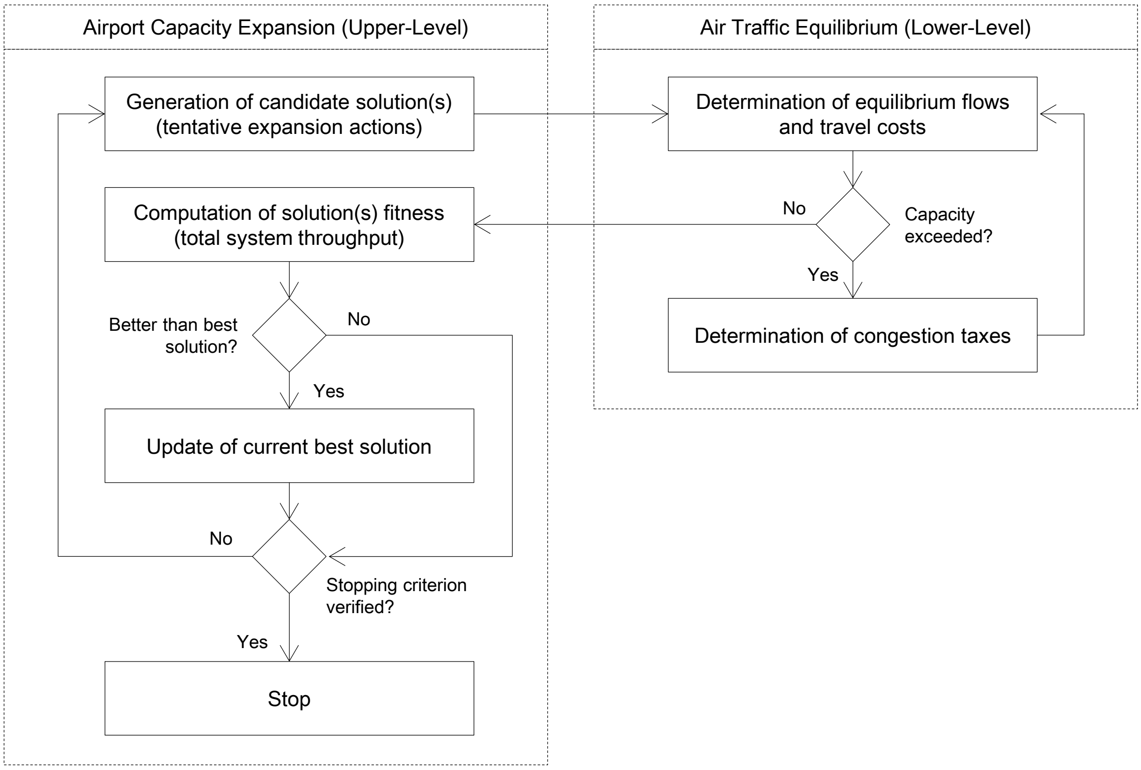

Figure 7 – Outline of the algorithm

The AIA comprises an Add procedure and an Interchange procedure. The Add procedure starts with the initial airport network and, in successive iterations, selects the one-level upgrade change that allows the best improvement of the objective function (or *fitness*), until no further improvement is possible. The Interchange procedure starts with the Add solution and, in successive iterations, selects the combination of one-level upgrade and downgrade changes that allows the best improvement of the objective function, until no further improvement is possible. These procedures are repeated sequentially while solutions keep improving, or until it is not possible to find more solutions within the budget available (the solutions generated during the search are always feasible with regard to the budget constraint). Solutions generated during the search are encoded in a string of N integer digits, representing the capacity level installed at the centers (ranging from 0, if the centers do not have airport, to |***M***|, if the maximum capacity is installed). The pseudo-code of the AIA is depicted in Figure 8 (for clarity sake, indexes of decision variables are not displayed).

```
INITIALIZATION:
1)  Set initial airports capacity, S, as current solution, Z^C:
        1.1) Z^C ← S
        1.2) fitness(Z^C) ← fitness(S)
2)  Set current solution, Z^C, as best solution, Z^B:
        2.1) Z^B ← Z^C
        2.2) fitness(Z^B) ← fitness(Z^C)
GENERATION OF CANDIDATE SOLUTIONS:
3)  Add:
        3.1) Upgrade the capacity of each airport in Z^C one-level
        3.2) Denote Z^N as the neighbor solution with the airport upgrade
             change that has the best fitness
        3.3) Move or not:
                  if fitness(Z^N) > fitness(Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C) ← fitness(Z^N)
                       move to 3)
                  else
                       move to 4)
                  end-if
4)  Interchange:
        4.1) Combine one-level upgrade and downgrade changes for each
             pair of airports in Z^C
        4.2) Denote Z^N as the neighbor solution with the airport upgrade
             and downgrade changes that has the best fitness
        4.3) Move or not:
                  if fitness(Z^N) > fitness(Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C) ← fitness(Z^N)
                       move to 4)
                  else
                       move to 5)
                  end-if
STOPPING CRITERIA:
5)  Update best solution or stop search:
        if fitness(Z^C) > fitness(Z^B) then
             move to 2)
        else
             STOP.
        end-if
```

Figure 8 – Pseudo-code of the Add+Interchange algorithm

The DIA is very similar to the AIA, but it comprises a Drop procedure instead of an Add procedure. The Drop procedure starts by setting the maximum admissible capacity for all airports and, in successive iterations, selects the one-level downgrade airport change that allows the best improvement of the objective function. In this case, the objective function comprises a penalty for each unit of expenditure above the budget available (*penalty* x δb). The pseudo-code of the DIA is depicted in Figure 9.

```
INITIALIZATION:
1)  Set maximum feasible capacities, Z^max, for all airports and define
    it as current solution, Z^C:
        Z^C ← Z^max
        fitness(Z^C, δb|Z^C) ← fitness(Z^max, δb|Z^max)
2)  Set current solution, Z^C, as best solution, Z^B:
        Z^B ← Z^C
        fitness(Z^B, δb|Z^B) ← fitness(Z^C, δb|Z^C)
GENERATION OF CANDIDATE SOLUTIONS:
3)  Drop:
        3.1) Downgrade the capacity of each airport in Z^C one-level
        3.2) Denote Z^N as the neighbor solution with the airport
             downgrade change that has the best fitness
        3.3) Move or not:
                  if fitness(Z^N, δb|Z^N) > fitness(Z^C, δb|Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C, δb|Z^C) ← fitness(Z^N, δb|Z^N)
                       move to 3)
                  else
                       move to 4)
                  end-if
4)  Interchange:
        4.1) Combine one-level upgrade and downgrade changes for each
             pair of airports in Z^C
        4.2) Denote Z^N as the neighbor solution with the airport upgrade
             and downgrade changes that has the best fitness
        4.3) Move or not:
                  if fitness(Z^N, δb|Z^N) > fitness(Z^C, δb|Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C, δb|Z^C) ← fitness(Z^N, δb|Z^N)
                       move to 4)
                  else
                       move to 5)
                  end-if
STOPPING CRITERIA:
5)  Update best solution or stop search:
        if fitness(Z^C, δb|Z^C) > fitness(Z^B, δb|Z^B) then
             move to 2)
        else
             STOP.
        end-if
```

Figure 9 – Pseudo-code of the Drop+Interchange algorithm

2.1.2 Variable neighborhood search algorithms

Local search algorithms have the disadvantage of easily getting trapped in local optima, potentially far from a global optimum. A possible manner of dealing with this is to use a systematic change of neighborhood structures during the search in order to explore solutions increasingly distant from the incumbent solution (Hansen and Mladenović, 2001). This approach is called variable neighborhood search. Three variable neighborhood search algorithms are considered: Classic Variable Neighborhood Search algorithm (VNSA), Variable Neighborhood Descent algorithm (VNDA1), and Exhaustive Variable Neighborhood Descent algorithm (VNDA2).

The VNSA starts with the initial airport network, generates a random solution within the neighborhood space defined by the first of a pre-defined set of neighborhood structures ("shaking"), and evolves from this neighboring solution to a local optimum using a local search procedure. If the local optimum found is better than the current best solution, the best solution is updated and the solution search restarts. Otherwise, the neighborhood space is changed according to the following neighborhood structure, a new neighboring solution is randomly generated, and a local search is performed. This sequence is repeated until there are no more neighborhood structures to examine. Four neighborhood structures were considered for this application: *i*) one-level upgrade change for one airport; *ii*) two-levels upgrade change for one airport; *iii*) combination of one-level upgrade and downgrade changes for two airports; and *iv*) one-level upgrade change for two airports. The local search was performed by successively applying a sequence of Drop, Add and Interchange procedures (see Sub-section 2.1.1). The pseudo-code of the VNSA is depicted in Figure 10.

```
INITIALIZATION:
1)  Set initial airports capacity, S, as best solution, Z^B:
        2.1) Z^B ← S
        2.2) fitness(Z^B) ← fitness(S)
2)  Select the set of neighborhood structures N^k (k = 1,…,k^max) that
    will be used in the search
3)  k ← 1
GENERATION OF CANDIDATE SOLUTIONS:
4)  Shaking of best solution at neighborhood k:
        4.1) Select random solution, Z^N_k, from the k^th neighborhood of
             current best solution
        4.2) Set neighbor solution, Z^N_k, as current solution, Z^C:
                  Z^C ← Z^N_k
                  fitness(Z^C) ← fitness(Z^N_k)
5)  Local search:
        5.1) Perform local search from current solution, Z^C, and denote
             local optimum found as Z^N
        5.2) Move or not:
                  if fitness(Z^N) > fitness(Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C) ← fitness(Z^N)
                  end-if
STOPPING CRITERIA:
7)  Update best solution or change neighborhood structure:
        if fitness(Z^C) > fitness(Z^B) then
             Z^B ← Z^C
             fitness(Z^B) ← fitness(Z^C)
             k ← 1
             move to 4)
        else-if fitness(Z^C) ≤ fitness(Z^B) and k < k^max then
             k ← k+1
             move to 4)
        else
             STOP.
        end-if
```

Figure 10 – Pseudo-code of the Classic Variable Neighborhood Search algorithm

If the selection of neighboring solutions is not performed through randomization, but through exhaustive exploration of neighborhood, the Variable Neighborhood Search Algorithm is transformed into the Variable Neighborhood Descent Algorithm (VNDA1). The VNDA1 starts with the initial airport network, evaluates all solutions within the neighborhood space defined by the first of the set of neighborhood structures under consideration, and evolves from the best neighboring solution to a local optimum using a local search procedure. If the local optimum found is better than the current best solution, the best solution is updated and the solution search restarts. Otherwise, the neighborhood space is changed according to the following neighborhood structure and the search continues. This sequence is repeated until there are no more neighborhood structures to examine. The pseudo-code of the VNDA1 is depicted in Figure 11.

```
INITIALIZATION:
1)  Set initial airports capacity, S, as best solution, Z^B:
       2.1) Z^B ← S
       2.2) fitness(Z^B) ← fitness(S)
2)  Select the set of neighborhood structures N^k (k = 1,…,k^max) that
    will be used in the search
3)  k ← 1
GENERATION OF CANDIDATE SOLUTIONS:
4)  Exploration of neighborhood k:
       4.1) Evaluate all solutions within the neighborhood space
            defined by the k^th neighborhood structure
       4.2) Denote the best solution obtained as Z^N_k
       4.3) Set best neighbor solution, Z^N_k, as current solution, Z^C:
                 Z^C ← Z^N_k
                 fitness(Z^C) ← fitness(Z^N_k)
5)  Local search:
       5.1) Perform local search from current solution, Z^C, and denote
            local optimum found as Z^N
       5.2) Move or not:
                 if fitness(Z^N) > fitness(Z^C) then
                      Z^C ← Z^N
                      fitness(Z^C) ← fitness(Z^N)
                 end-if
STOPPING CRITERIA:
7)  Update best solution or change neighborhood structure:
       if fitness(Z^C) > fitness(Z^B) then
            Z^B ← Z^C
            fitness(Z^B) ← fitness(Z^C)
            k ← 1
            move to 4)
       else-if fitness(Z^C) ≤ fitness(Z^B) and k < k^max then
            k ← k+1
            move to 4)
       else
            STOP.
       end-if
```

Figure 11 – Pseudo-code of the Variable Neighborhood Descent algorithm

The VNDA2 is a variant of the VNDA1, but, instead of applying a local search procedure to find the local optimum within each neighbor, it uses an intensive exploration of the solution space among all neighborhood structures before each move. Therefore, the VNDA2 starts with the initial airport network and, in successive iterations, explores all solution space within the set of pre-defined neighborhood structures. If the best neighbor solution (among all neighborhood structures) is better than the current incumbent solution, the latter is updated and the search restarts. The outline of the VNDA2 is depicted in Figure 12.

2.1.3 Genetic algorithms

As opposed to local search and variable neighborhood search algorithms, which follow a solution path defined through neighborhood structures around a single solution, genetic algorithms work with a population of solutions (called chromosomes or individuals in this context) whose fitness improves in consecutive iterations (generations) through the recombination of the attributes of current solutions (Holland, 1992). Two genetic algorithms are considered: Classic Genetic algorithm (GA1) and Hybrid Genetic algorithm (GA2).

```
INITIALIZATION:
1)  Set initial airports capacity, S, as best solution, Z^B:
        2.1) Z^B ← S
        2.2) fitness(Z^B) ← fitness(S)
2)  Select the set of neighborhood structures N^k (k = 1,…,k^max) that
    will be used in the search
GENERATION OF CANDIDATE SOLUTIONS:
3)  Exploration of neighborhoods:
        3.1) Evaluate all solutions within the neighborhood spaces in N^k
        3.2) Denote the best solution in the k^th neighborhood structure
             as Z^N_k
        3.3) Denote the best neighbor solution as Z^N*
        3.4) Set best neighbor solution, Z^N*, as current solution, Z^C:
                  Z^C ← Z^N*
                  fitness(Z^C) ← fitness(Z^N*)
4)  Local search:
        4.1) Perform local search from current solution, Z^C, and denote
             local optimum found as Z^N
        4.2) Move or not:
                  if fitness(Z^N) > fitness(Z^C) then
                       Z^C ← Z^N
                       fitness(Z^C) ← fitness(Z^N)
                  end-if
STOPPING CRITERIA:
5)  Update best solution or change neighborhood structure:
        if fitness(Z^C) > fitness(Z^B) then
             Z^B ← Z^C
             fitness(Z^B) ← fitness(Z^C)
             k ← 1
             move to 3)
        else-if fitness(Z^C) ≤ fitness(Z^B) and k < k^max then
             k ← k+1
             move to 3)
        else
             STOP.
        end-if
```

Figure 12 – Pseudo-code of the Exhaustive Variable Neighborhood Descent algorithm

The Classic Genetic algorithm (GA1) starts by generating a random population of solutions, which is updated in consecutive iterations through three procedures: selection, crossover and mutation, performed sequentially in this order. The selection procedure consists on the selection of solutions from the previous population to compose the new population. The selection process is made with regard to the probability that a given solution is chosen among the remaining solutions, which is higher for the best solutions and lower for the worst solutions ("stronger" individuals have more chances to prevail). In the crossover procedure, pairs of chromosomes chosen at random are split at a random position (or gene, representing a given airport within the airport network) and combined with a given probability, p_c. In the mutation procedure, each center (or gene) is changed with a given probability, p_m. The change can be performed by increasing the capacity one level or by decreasing the capacity one level (with equal probability, $p_m/2$). The solutions obtained in the crossover and mutation procedures substitute the original solutions in the current population. Finally, the solutions obtained are adjusted through a Drop procedure in order to eliminate the unnecessary capacity. At the end of each iteration, the solutions of the current population are evaluated. Solutions that violate the budget constraint are allowed but their value comprises a penalty for each unit of expenditure above the budget available. The best solution obtained in each iteration is kept as new incumbent solution if it is better than the previous incumbent solution. This process is repeated until the incumbent solution does not change in a given number of consecutive iterations. The pseudo-code of the GA1 is depicted in Figure 13.

GA2 is very similar to the GA1, but includes a local search procedure at fixed iteration intervals. The local search is performed with the best solution of the current population as initial solution. The local search includes a Drop procedure to repair unfeasible solutions in respect to the budgetary constraints, and an Add procedure to exploit the budget available. If the local optimum found through the local search is better than the best solution, the best solution is updated and replaces the best solution of the current population.

```
INITIALIZATION:
1)  Generate an initial population of random solutions, POP^0 (Z^0_1, Z^0_2,
    …, Z^0_dim)
2)  FITNESS^0 (fitness(Z^0_1, δb),…, fitness(Z^0_dim, δb)) ← evaluate (POP^0)
3)  Rank solutions by decreasing value of fitness
4)  Set best solution of the population, Z^0_1, as best solution, Z^B:
        Z^B ← Z^0_1
        fitness(Z^B, δb) ← fitness(Z^0_1, δb)
5)  t ←1
UPDATE OF POPULATION:
6)  Selection:
        6.1) Define selection probability for each solution j in
             population POP^(t-1)
        6.2) probability^(t-1)_i = (fitness^(t-1)_(j-1) - fitness^(t-1)_j) /
             sum(k in dim) fitness^(t-1)_k
        6.3) Compose population POP^t with solutions from population t-1,
             according to the selection probabilities, probability^(t-1)
7)  Crossover:
        7.1) Cross pairs of random solutions in POP^t at a random
             position with probability p_c
        7.2) The solutions obtained substitute the original solutions in
             POP^t
8)  Mutation:
        8.1) Change genes within POP^t with probability p_m, by increasing
             or decreasing correspondent capacity by one level with
             probability p_m/2
        8.2) The solutions obtained substitute the original solutions in
             POP^t
9)  Evaluation of current population:
        FITNESS^t ← evaluate (POP^t)
        Rank solutions by decreasing value of fitness
STOPPING CRITERIA:
10) Update best solution:
        if fitness(Z^t_1) > fitness(Z^B) then
             Z^B ← Z^t_1
             fitness(Z^B, δb) ← fitness(Z^t_1, δb)
             t ←0
        else
             t ← t+1
        end-if
11) if t < t_max then
        move to 6)
    else
        STOP.
    end-if
```

Figure 13 – Pseudo-code of the Classic Genetic algorithm

2.2 Air traffic equilibrium

The assessment of the candidate solutions generated during the search is made with regard to the equilibrium traffic flows and travel costs in the network. The simulation of the equilibrium in the network is made along with the computation of the congestion taxes to apply for the airports if the capacity of the airports is not enough to accommodate all demand.

Initially, the congestion taxes are set to set zero for all airports, and the equilibrium is simulated assuming that the capacity of the airports can be violated (yet, travel costs are still dependent on the airports utilization rate). The simulation of the equilibrium starts by calculating the travel costs as given by constraints (10) assuming free-flow conditions (the variable cost component of airport costs is set to zero and leg costs are only dependent on travel distance). Then, the aggregate O-D demand between cities is computed and assigned to the itineraries, as given by constraints (8) and (7) respectively, with regard to the current travel costs. With the new traffic flows in the itineraries, the traffic flows in the legs and in the airports are computed as defined by constraints (6) and (5), respectively. If convergence is achieved (i.e., traffic flows in the legs do not change, except for a small tolerance, *tol*), the simulation of the equilibrium is finished; otherwise, travel costs and traffic flows are updated using the method of successive averages (Robbins and Monro, 1951; Powell and Sheffi, 1982). After the simulation of the equilibrium, if the capacity of none of the airports is violated, the solution is evaluated; otherwise, a set of trial congestion taxes are computed through the multiple line search method and the equilibrium is again simulated. The multiple line search method consists on successively increasing and decreasing the current taxes by a small amount, and, through a simple linear extrapolation, determines the tax that is needed to keep demand below traffic. This iterative process is repeated while the objective function keeps improving, and until the capacity of none of the airports is violated – the goal is to find the set of congestion taxes which maximizes demand served within the airport network for the current airport capacities, while ensures that the capacity of the airports is not violated. The pseudo-code of the algorithm is given in Figure 14.

The performance of the line search method in identifying "good" arrangements for the taxes was tested by comparing the results obtained for a set of 20-airports test instances with the ones obtained by a local search procedure. The local search procedure developed consists on a sequence of Add and Drop routines, which successively select the best tax increase and decrease (by a given amount, *step*) with regard to the value of the objective function. The two routines are applied sequentially while the objective function keeps improving, and until the capacity of none of the airports is violated. The results obtained by both algorithms are shown in Figure 15a and Figure 15b, respectively for a situation in which 20% of the airports are hub airports, and for a situation in which 40% of the airports are hub airports (see Sub-section 3.1 for a description of the test instances). The line search procedure identified almost always the best arrangements for the taxes at a little computation effort, taking in average 4.7 seconds. The local search procedure performed better for smaller tax increments, however, the computational burden was higher (took in average 18.6, 30.0 and 47.2 seconds considering a step of $2, $1 and $0.5 respectively).

```
INITIALIZATION:
1)  Set airports capacity, Z, according to current candidate solution
2)  it ← 0
3)  Set current congestion taxes, X_it, equal to zero for all airports
SIMULATION OF EQUILIBRIUM:
4)  n ← 0
5)  Set initial (n=0) traffic flows equal to zero:
        V_0 ← 0
        U_0 ← 0
        W_0 ← 0
6)  n ← n +1
7)  Compute travel costs for the itineraries, C_n, as a function of the
    traffic flows in the legs and in the centers at iteration n-1 (U_n-1
    and W_n-1, respectively)
8)  Compute aggregate O-D demand between centers, Q_n, as a function of
    the current travel costs, C_n
9)  Weight aggregate O-D demand at the current iteration with aggregate
    O-D demand at the previous iteration:
        Q_n ← (1-1/n). Q_n-1 -1 + (1/n).Q_n
10) Compute the traffic flow in the itineraries, legs and centers at
    the current iteration (V_n, U_n and W_n, respectively)
11) Assessment of equilibrium:
        If U_n < U_n.tol or U_n > U_n.tol then
             move to 6)
        else
             move to 12)
        end-if
11) Assessment of solution for current taxes:
        fitness(Z, X_it) ← evaluate (Z, X_it)
COMPUTATION OF THE CONGESTION TAXES:
12) it ← it + 1
13) Increase tax in X_it-1 for each capacity violated center by 1% and
    simulate equilibrium
14) Using linear extrapolation, compute the tax to apply for each
    center so that the utilization ratio equals one
15) Decrease tax for each airport by 1% and simulate equilibrium
16) Using linear extrapolation, compute the tax to apply for each
    airport so that the utilization ratio equals one
17) Define current taxes, X_it, by summing the individual taxes obtained
    previously
18) if fitness(Z, X_it) if better that fitness(Z, X_it-1) then
        move to 12)
    else
        STOP.
    end-if
```

Figure 14 – Simulation of the equilibrium and computation of the congestion taxes

3. Computational study

This section provides a comparison between the algorithms developed to generate candidate solutions (described in Sub-section 2.1). The algorithms are compared from the standpoint of solution quality and computation effort through their application to a large sample of randomly generated test instances with different sizes. The section starts with the description of the test instances (which are the same ones used in Chapter 2 to illustrate the applicability of the model). Then, the performance of the algorithms is assessed in the light of solution quality and computation effort. The optimal solutions can only be obtained for small-sized test instances through complete enumeration. The assessment of the solutions obtained by the algorithms is made with regard to the optimal solutions when known, and to the known best solutions (optimal or sub-optimal) for larger test instances.

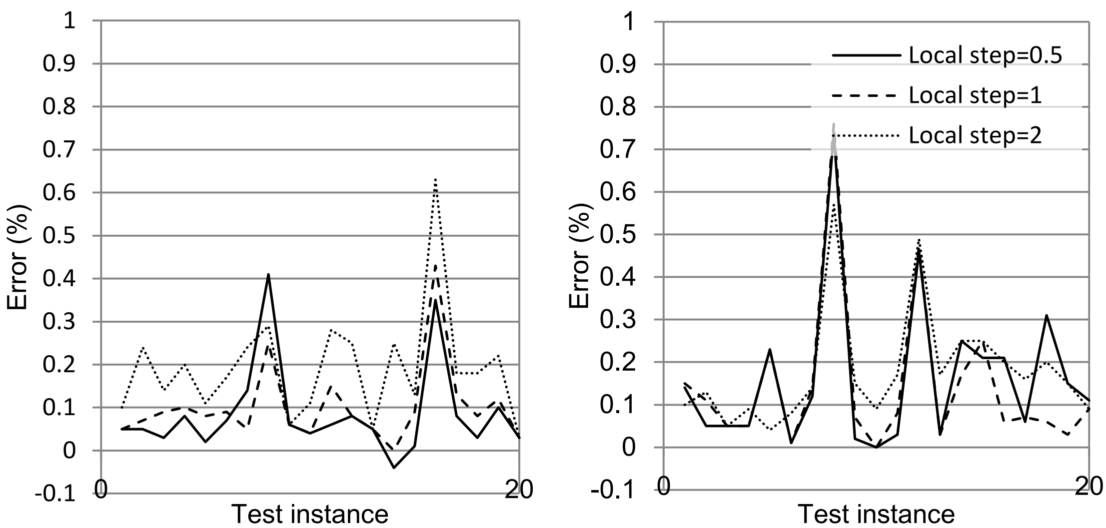

Figure 15 – Comparison between the solutions obtained with the local search and with the line search procedures, with (a) 20% and (b) 40% of the airports defined as hub airports

3.1 Test instances

The test instances are based on a region of 4,000 × 4,000 km^2, and differ by the number of centers, the location of the centers, and the population of the centers. 20 random instances with 10 and 20 centers, and 5 instances with 30 centers, are considered. The centers are randomly distributed over the region, and the populations of the centers are assumed to follow the Zipf rank-size rule considering the maximum population of 20 million for the largest center.

All centers are currently served by airports. The airports of the h% largest centers (Centers #1 to #$h.|\boldsymbol{N}|$) are hub airports, and other airports are non-hub airports, serving only as trip origins or destinations. The initial capacity of the airports was determined by solving the model with no budget constraints. The airports can have six possible layouts. The possible layouts and corresponding airport capacities are listed in Table 16, and the expansion costs are given in Table 17. The minimum traffic flow required to justify the existence of a flight leg is 500 pax/day. The masses of the population centers are assumed to grow by 25% until the design year. The values of the model parameters are the same considered in Chapter 2.

Table 16 – Possible airport layouts and corresponding increase in capacity (x10^3 pax/day)

Layout	Runway configuration	Capacity (10^3 pax/day)
1	Single runway	40
2	Two close parallel runways	60
3	Two medium spaced parallel runways	70
4	Two independent parallel runways	80
5	Three runways (two close runways plus one)	100
6	Four runways (two pairs of close parallel runways)	120

Table 17 – Airport expansion costs (x10^8 $)

Cost (10^8 $)						
Initial airport layout	Final airport layout					
	1	2	3	4	5	6
No airport	8	10	12	14	16	18
1	-	6	8	9	12	14
2	-	-	5	6	9	11
3	-	-	-	4	7	9
4	-	-	-	-	6	8
5	-	-	-	-	-	5

3.2 Study Results

The quality of the solutions provided by the algorithms, and corresponding computational effort required to solve the model, are synthetized in Table 18 and Table 19, respectively for a situation with no budget constraints and for a situation with half of the budget needed to eliminate congestion problems.

The solutions provided for the genetic algorithms were obtained considering the following values for the parameters: *dim* (size of the population) = 2|***N***|, p_c (probability of crossover) = 50%, p_m (probability of mutation) = 50%, t^{max} (maximum number of iterations with no improvement) = 14, and *penalty* (penalty for unit of budget exceeded) = 15 for GA1; and *dim* = 0.5|***N***|, p_c = 25%, p_m = 75%, t^{max} = 30, *penalty* = 15, and it_{local} (iterations with local search) = 5 for GA2. These values were determined by comparing the results obtained for 10 instances with 20 airports (Seeds #1 to #10), with 20 random set of values for the parameters. The following values for the parameters were admitted: *dim* $\mathcal{E}$ {0.5|***N***|, 1|***N***|, 2|***N***|}, p_c $\mathcal{E}$ {25%, 50%, 75%}, p_m $\mathcal{E}$ {25%, 50%, 75%}, t^{max} $\mathcal{E}$ {10, 20, 30}, *penalty* ℇ {5, 10, 15}, and it_{local} ℇ {5, 10, 15}. The selection of the values set was made with regard to the number of best solutions found.

The values reported for the algorithms with randomization (VNSA, GA1 and GA2) are the result of five runs with random search seeds. All algorithms were coded in Mosel (FICO™ Xpress Optimization Suite) and the computations were made on an Intel® Core™ i7 CPU, Q740 1.73 GHZ with 8.00 GB of RAM.

Table 18 – Summary of the results for a situation with no budget constraints

N	Solution algorithm	Percentage of hub airports					
		20			40		
		CPU [secs]	Best solutions [%]	Max. Deviation [%]	CPU [secs]	Best solutions [%]	Max. Deviation [%]
10	AIA	1.9	100%	0.0%	5.1	100%	0.0%
	DIA	0.4	100%	0.0%	0.5	100%	0.0%
	VNSA	2.5	100%	0.0%	5.9	100%	0.0%
	VNDA1	2.0	100%	0.0%	5.4	100%	0.0%
	VNDA2	3.3	100%	0.0%	14.6	100%	0.0%
	GA1	47.7	100%	0.7%	66.7	100%	0.6%
	GA2	40.8	100%	0.0%	58.3	100%	0.0%
20	AIA	51.3	100%	0.0%	83.6	100%	0.0%
	DIA	11.4	100%	0.0%	10.3	100%	0.0%
	VNSA	58.7	100%	0.0%	86.5	100%	0.0%
	VNDA1	51.7	100%	0.0%	85.1	100%	0.0%
	VNDA2	146.8	100%	0.0%	338.0	100%	0.0%
	GA1	1249.2	100%	0.9%	1367.8	100%	0.0%
	GA2	837.8	100%	0.0%	979.7	100%	0.0%
30	AIA	300.6	100%	0.0%	741.2	80%	0.1%
	DIA	77.4	100%	0.0%	238.1	80%	1.1%
	VNSA	330.2	100%	0.0%	705.5	60%	0.1%
	VNDA1	301.8	100%	0.0%	693.0	80%	0.1%
	VNDA2	1044.2	100%	0.0%	4853.4	80%	0.1%
	GA1	7554.8	100%	0.0%	5810.4	40%	0.5%
	GA2	5038.7	100%	0.0%	6508.5	100%	0.0%

Table 19 – Summary of the results for a situation with budget constraints

N	Solution algorithm	Percentage of hub airports					
		20			40		
		CPU [secs]	Best solutions [%]	Max. Deviation [%]	CPU [secs]	Best solutions [%]	Max. Deviation [%]
10	Optimal	69.5	-	-	175.3	-	-
	AIA	1.7	100%	0.0%	5.1	90%	1.2%
	DIA	1.6	85%	6.5%	3.5	70%	2.7%
	VNSA	8.3	100%	0.0%	17.5	100%	0.0%
	VNDA1	1.8	100%	0.0%	5.5	90%	1.2%
	VNDA2	2.4	100%	0.0%	10.8	100%	0.0%
	GA1	59.1	100%	0.0%	92.2	100%	0.0%
	GA2	55.0	100%	0.0%	79.9	100%	0.8%
20	AIA	45.9	65%	1.5%	78.1	75%	1.7%
	DIA	54.3	55%	4.7%	79.2	50%	6.1%
	VNSA	121.6	70%	3.2%	173.9	80%	2.5%
	VNDA1	46.0	65%	1.5%	79.2	75%	1.7%
	VNDA2	96.6	70%	1.5%	236.5	95%	1.7%
	GA1	1672.2	90%	1.4%	1975.0	70%	1.1%
	GA2	1243.0	100%	0.0%	1076.3	80%	0.9%
30	AIA	234.0	20%	2.7%	545.0	0%	1.9%
	DIA	378.9	40%	0.5%	630.7	40%	3.6%
	VNSA	476.3	0%	2.7%	742.4	80%	0.3%
	VNDA1	233.3	20%	2.7%	539.2	0%	1.9%
	VNDA2	581.9	60%	0.1%	2632.1	20%	1.2%
	GA1	11396.2	40%	1.2%	13346.0	60%	1.0%
	GA2	8004.0	100%	0.0%	8403.3	80%	0.1%

For the situation with no budget constraint, all algorithms provided the same solution for all test instances except for 30-airports instances with 40% of the airports defined as hubs. GA2 found the best solution for all cases (which may not be a global optimum), whereas the remaining algorithms failed to identify the best solution for at least one instance. The DIA was by far the fastest, taking on average less than 1 second, a little more than 10 seconds, and a little less than 4 minutes to solve 10-, 20-, and 30-airport instances, respectively. Only once, it failed to identify the best solution, but when it failed (for one of the five 30-airport instances) it was more distant to the best solution than all the other algorithms. The classic local search and variable neighborhood search algorithms took, on average, less than 10 minutes to solve all instances, except VNDA2, which spent almost 50 minutes to solve the 30-airport instances. The genetic algorithms took considerably more time to solve the model: around 1 and 20 minutes to solve the 10- and 20-airport instances, respectively, and about 2 hours to solve the 30-airport instances.

For the situation with a budget constraint, GA2 also provided the best results, only failing to identify the best solutions for 5 instances, with a maximum deviation of 0.9%. In particular, it always found the optimum solution for the 10-airport instances (which, in this case, we were able to determine through complete enumeration). VNSA, VNDA2, and GA1 provided good results for the 10- and 20-airport instances, identifying the best solutions in about 90% of the cases (maximum deviations of 3.2%, 1.7%, and 1.4%, respectively). GA1 also identified the best solutions for all 30-airport instances, whereas VNSA and VNDA2 only failed to identify the best solution for one instance (maximum deviations of 2.7% and 1.2%). The results obtained through AIA, DIA and VNDA1 were much worse. Indeed, DIA only found 62% of the best solutions, and AIA and VNDA1 about 74% (maximum deviations of 6.5, 2.7, and 2.7). The classic local search and variable neighborhood search algorithms took less than 3 minutes to solve the 20-airport instances, and less than 10 minutes to solve the 30-airports instances, except VNDA2 which took about 25 minutes. The genetic algorithms required again considerable more time to solve the model: between 10 minutes and 1 hour to solve the 20-airport instances, and between 1.5 and 6 hours to solve the 30-airport instances.

Overall, it can be said that all algorithms will perform rather well in the absence of budget constraints, but some of them are unreliable in the presence of such constraints. The best compromise between solution quality and computation effort seems to be provided by VNDA2 when there is no budget constraint and VNSA when there is. Among the fastest algorithms, DIA provides solutions clearly worse than AIA and VNDA1. If CPU time is not an issue, then GA2 would be preferable. Also, it can be said that, even when GA2 is used for a 30-airport instance (which is approximately the size of the main airport network of the US), the computation effort is still quite reasonable given the strategic nature of the problem being dealt with.

4. Conclusion

The airport network capacity expansion problem is to find the best set of expansion actions to implement for an airport network in order to cope with future demand in the best possible way, while complying with a given budget. The problem was formulated in Chapter 2 in a nonlinear mixed integer optimization model. The model is very difficult to solve using exact solution methods. Therefore, a bi-level heuristic method was proposed to solve the model: the upper-level component generates candidate expansion actions to apply to the airport network (candidate solutions), which are, in turn, assessed after simulating the equilibrium traffic flows and travel costs in the network in the lower-level component.

In this chapter, the solution method is explained in more detail, and several heuristic algorithms are proposed to generate candidate solutions. Seven algorithms were implemented: Add & Interchange Algorithm, Drop & Interchange Algorithm, Variable Neighborhood Search Algorithm, Classic Variable Neighborhood Descent Algorithm, Exhaustive Variable Neighborhood Descent Algorithm, Classic Genetic Algorithm, and Hybrid Genetic Algorithm. The algorithms were compared with regard to solution quality and computational effort through their application to a sample of 10-, 20- and 30-airports test instances, both for a situation with no budget constraints and for a situation with budget constraints. The 10-airports instances were also solved by complete enumeration for the situation with budget constraints.

All algorithms provided the same solution for the 10- and 20-airports instances for a situation with no budget constraints. For the 30-airports instances with 40% of the airports defined as hubs, only the Hybrid Genetic Algorithm found the best solution for all cases, whereas the remaining algorithms failed to identify the best solution for at least one instance. For a situation with budget constraints, the Hybrid Genetic Algorithm also provided the best results, only failing to identify the best solutions for 5 instances. The Classic Genetic Algorithm, the Variable Neighborhood Search Algorithm, and the Enhanced Variable Neighborhood Descent Algorithm also provided good results, whereas the Add and Interchange Algorithm, the Drop and Interchange Algorithm, and the Classic Variable Neighborhood Descent Algorithm provided poor results. The local search algorithms and the variable neighborhood search algorithms were relatively fast to solve the model even for larger instances, whereas the genetic algorithms took considerable more time.

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Chapter 4

Study on the Long-Term Evolution of the Airport Network of the United States

1. Introduction

The air transportation industry is of vital importance for the mobility of people and for the development of the economy everywhere in the world and particularly in the United States (US) (Ishutkina and Hansman 2009). As of 2010, the US air transportation system handled 786.7 billion passenger-miles and 35.9 billion freight ton-miles (FAA 2011a). It is estimated that the industry contributes about 1.3 trillion USD per year to the national economy (roughly 5% of the country's GDP) and supports about 10.2 million jobs (FAA 2011b).

The strong development of the US economy over the last three decades, together with the deregulation of the air transportation industry in 1978 (de Neufville and Odoni 2003), have led to a steady growth of air traffic flows. The total number of enplanements increased by a factor of 3 from 236 million in 1976 to 702 million in 2010, corresponding to an average annual rate of 3.3% (FAA 2012a, TAF). The increase in traffic has not been accompanied by an adequate increase of airport capacity, which has caused the escalation of congestion problems and flight delays at several airports across the country. It is estimated that, by 2007, the total direct costs associated with flight delays (including costs incurred by airlines and passengers, and costs from lost demand) was about 28.9 billion USD. In addition to these direct costs imposed on airlines and passengers, delays are estimated to have reduced GDP by 4 billion USD (NEXTOR 2010).

After 2008, because of the economic problems that have affected the US economy, air traffic growth has slowed down. However, long-term forecasts indicate that demand for air transportation will continue to increase at a significant pace (FAA 2011a, Boeing 2010), and, consequently, capacity shortage problems are expected to worsen in the upcoming years at the key airports. According to the FAA's FACT 2 study (FAA 2007), developed to identify airports and metropolitan areas that are likely to need additional capacity in the future, congestion problems will seriously affect 18 airports and 7 metropolitan areas by 2015, and 27 airports and 15 metropolitan areas by 2025 if no actions are taken.

Airport congestion problems can be dealt with from the demand side, through demand management mechanisms, and from the supply side, through scaling mechanisms (Bonnefoy and Hansman 2008). Demand management mechanisms address the demand/supply imbalance either through regulatory measures (e.g. slot control) or market-based measures (e.g. congestion pricing). Scaling mechanisms improve supply either by augmenting the efficiency of operations (e.g. increase of aircraft size) or by increasing the capacity of airport infrastructures, through the improvement of air traffic management systems, the expansion of existing airports, and the construction of new airports. The improvement of air traffic management systems may accommodate some increase in traffic, as foreseen by FAA in its NextGEN Implementation Plan (FAA 2012b). However, in the long term, the expansion of existing airports and the construction of new airports may be necessary to deal with the growing volumes of air traffic and attenuate the escalation of congestion problems.

This chapter presents the results of a study concerned with the long-term evolution of the network of major airports in the US. The study analyzes the impact of the increase of demand for air transportation on the performance of the country's airport network. In addition, using the optimization model introduced in Chapter 2, it determines the expansion actions to apply to the airports in order to maximize total system throughput for a given budget, taking into account the impact of airport congestion on travel cost and demand. Expansion actions consist of the expansion of existing airports (e.g. through the addition of new runways or the reconfiguration of existing runways) and the construction of new airports.

The model used in the study addresses airport expansion and/or construction problems from a network perspective. Such a perspective is not very common, particularly in the optimization-based literature. Common approaches consist of analyzing the economic impact of building or expanding one airport (e.g. Cohen and Coughlin 2003), comparing alternative locations for building a new airport through cost-benefit or multi-criteria analysis (e.g. Jorge and de Rus 2004 for the former and Vreeker et al. 2002 for the latter), and examining how proposed airport improvements affect system performance using queuing and other simulation models (e.g. Odoni et al. 1997).

To the best of our knowledge, Saatcioglu (1982) is the only study where a set of optimization models, derived from classic facility location analysis, are proposed to determine the optimum locations and capacities of airports within an airport network. However these models do not take into account supply-demand interactions. Some studies consider the impact of airport congestion on demand and on the traffic pattern within an airport network, but do not deal explicitly with airport expansion and/or construction problems. Hsiao and Hansen (2011) modeled passenger demand as a function of airport delay within the main airport network of the US and analyzed the impact of expanding Chicago O'Hare International airport. Ghobrial and Kanafani (1995) also focused on airport congestion problems within the context of an airport network, but analyzed the changes in hubbing patterns as a consequence of congestion. Evans and Schäfer (2011) focused on a network consisting of 22 airports of the US, and analyzed three different scenarios regarding its expansion. Their approach is based on an equilibrium analysis of five profit-seeking airlines which adapt their flight frequencies, aircraft size and flight network in response to airport congestion. Ferguson (2012) used a similar approach but considered a single airline with "benevolent" behavior, whose schedule is determined so as to optimize airport performance, and examined the effects on the airline of different combinations of airport capacity and fuel prices.

The chapter is organized as follows. In the next section, we briefly characterize the airport network of the US and identify the airports considered in the study. Afterward, we present the optimization model upon which our results are based and describe the solution method developed to handle it. This is followed by an explanation of how the statistical parameters included in the model were calibrated with US data. The results obtained through the model are then presented and discussed in the light of the FACT 2 study. The final section summarizes conclusions and identifies directions for further work.

2. Airport network

The National Plan of Integrated Airport Systems (NPIAS) classifies nearly 3,400 airports as being significant to national air transportation (FAA 2008). Despite this large number of airports, and as shown in Figure 16, the vast majority of air traffic is concentrated in a few key airports: about 70% of the total enplanements are handled at about 30 airports and 90% at 70 airports (FAA 2012a, OPSNET).

The concentration of traffic in a small number of airports, which is partly due to the widespread use of hub-and-spoke network configurations by the airlines, leads to an inadequate throughput at a number of key airports with implications on the performance of the whole airport network. These key airports are the 35 airports currently tracked in the FAA's Operational Evolution Plan (OEP). In 2008, they were characterized by the highest percentages of late arrivals, ranging from 15.8% at Lambert-St. Louis airport to 32.7% at Newark airport (FAA 2012a, ASPM and ASQP).

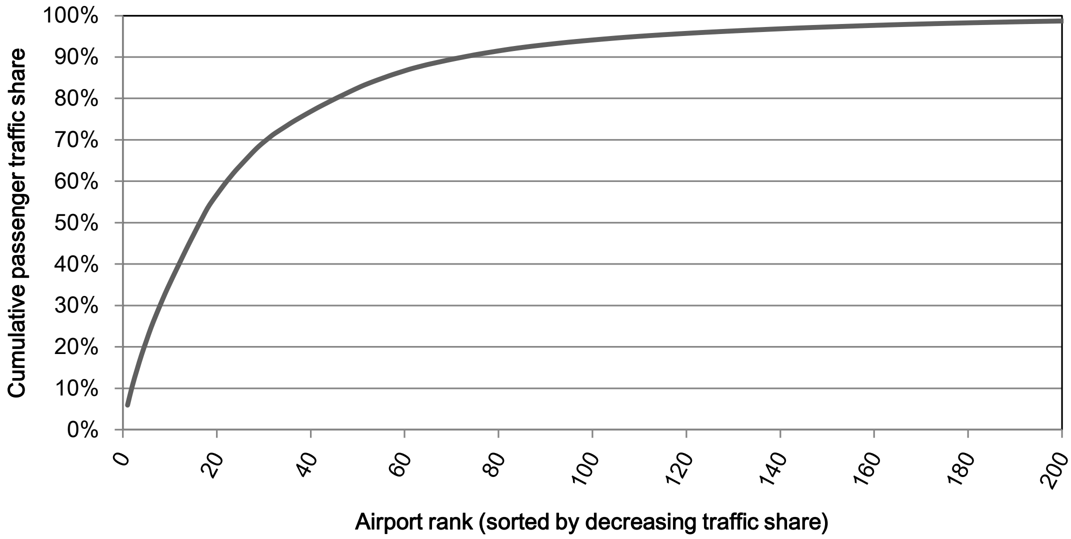


Figure 16 – Cumulative traffic at the NPIAS airports

In our study, we have focused on the 35 OEP airports, which are distributed across 28 metropolitan areas. In order to capture the behavior of regional passenger demand in multi-airport systems, the secondary airports serving those metropolitan areas were also considered in the study (passengers may be willing to use secondary airports in order to avoid the congested primary airports). It was assumed that, for an airport to be considered part of a multi-airport system, it should be within one hour's drive (or approximately 60 miles) of one of the OEP airports, and serve more than 500,000 passengers per year. The airports and metropolitan areas considered in our study are listed in Table 20.

The busiest airports in 2008 were Atlanta Hartsfield-Jackson International (ATL), Chicago O'Hare (ORD), Dallas Fort Worth (DFW) and Denver International (DEN), serving on average 2.4, 2.1, 1.6 and 1.6 thousand aircraft movements per day, respectively. In aggregate terms, the metropolitan area of New York generated the largest amount of traffic – around 3 thousand movements per day across its four main airports (Newark EWR, Kennedy JFK, La Guardia LGA, and Islip ISP). The metropolitan areas of Chicago (served by the airports of Midway MDW and O'Hare ORD), Los Angeles (International LAX, Santa Ana SNA, Ontario ONT, Burbank BUR, and Long Beach LGB) and Atlanta also generated a large amount of traffic, respectively, 2.7, 2.5 and 2.4 thousand movements per day.

3. Optimization model

The study of the long-term evolution of the network of the principal US airports was based on the optimization model proposed in Chapter 2. This model applies to a set of metropolitan areas (or centers) served by airports or multi-airport systems with known initial capacities (multi-airport systems are treated as single airports with a capacity equal to the total capacity of the airports serving the metropolitan areas). The aim of the model is to find the expansion actions to apply to the centers in order to maximize total system throughput, while coping with future demand and complying with a given budget.

Table 20 – Set of metropolitan areas and airports

Metropolitan Area	Airport code	Airport name
Atlanta	ATL	Atlanta/ Hartsfield-Jackson Intl.
Boston	BOS	Boston/ Logan
	PVD	Boston/ Providence
	MHT	Boston/ Manchester
Washington	BWI	Washington/ Baltimore
	DCA	Washington/ Reagan
	IAD	Washington/ Dulles
Cleveland	CLE	Cleveland/ Hopkins
	CAK	Cleveland/ Akron-Canton
Charlotte	CLT	Charlotte/ Douglas
Cincinnati	CVG	Cincinnati/ Northern Kentucky Intl.
Denver	DEN	Denver/ International
Dallas	DFW	Dallas/ Fort Worth
	DAL	Dallas/ Love Field
Detroit	DTW	Detroit/ Metropolitan
	FNT	Detroit/ Bishop
New York	EWR	New York/ Newark
	JFK	New York/ Kennedy
	LGA	New York/ LaGuardia
	ISP	New York/ Islip
Miami	FLL	Miami/ Fort Lauderdale
	MIA	Miami/ International
Houston	IAH	Houston/ Intercontinental
	HOU	Houston/ Hobby
Las Vegas	LAS	Las Vegas/ McCarran Intl.
Los Angeles	LAX	Los Angeles/ International
	SNA	Los Angeles/ Santa Ana
	ONT	Los Angeles/ Ontario
	BUR	Los Angeles/ Burbank
	LGB	Los Angeles/ Long Beach
Orlando	MCO	Orlando/ International
	SFB	Orlando/ Sanford
Chicago	MDW	Chicago/ Midway
	ORD	Chicago/ O'Hare
Memphis	MEM	Memphis/ International
Minneapolis	MSP	Minneapolis/ St. Paul Intl.
Portland	PDX	Portland/ International
Philadelphia	PHL	Philadelphia/ International
	ACY	Philadelphia/ Atlantic City
Phoenix	PHX	Phoenix/ Sky Harbor Intl.
Pittsburgh	PIT	Pittsburgh/ International
San Diego	SAN	San Diego/International
Seattle	SEA	Seattle/ Sea-Tac
San Francisco	SFO	San Francisco/ International
	OAK	San Francisco/ Oakland
	SJC	San Francisco/ San Jose
Salt Lake	SLC	Salt Lake/ International
Saint Louis	STL	Saint Louis/ Lambert Intl.
Tampa	TPA	Tampa/ International
	SRQ	Tampa/ Sarasota
	PIE	Tampa/ St. Petersburg

The following notation was used:

Sets:

$\boldsymbol{N}$ - set of centers (metropolitan areas) or airports

$\boldsymbol{N}_{jkr}$ - set of centers included in route r connecting centers j and k

$\boldsymbol{L}$ - set of flight legs

$\boldsymbol{L}_j$ - set of legs with start point in center j

$\boldsymbol{L}_{jkr}$ - set of legs included in route r connecting centers j and k

$\boldsymbol{R}_{jk}$ - set of routes connecting centers j and k

$\boldsymbol{R}_l$ - set of routes containing flight leg l

$\boldsymbol{M}_j$ - set of expansion actions applicable to center j

Parameters:

p_j - population of center j

i_j - disposable income per capita of center j

d_{jk} - travel distance between centers j and k

ϕ_{jk} - modal split factor for centers j and k

s_j – initial airport capacity of center j

u^*_l - traffic flow on leg l with origin or destination in centers not included in $\boldsymbol{N}$

w^*_j - traffic flow in center j with origin, connection or destination in centers not included in $\boldsymbol{N}$

g_{jm} - capacity increase in center j due to the application of expansion action m

e_{jm} - cost of applying expansion action m to center j

b - budget available for expansion actions

$\alpha, \mu, \varphi, \beta, \gamma, \sigma, \upsilon, \varpi, \theta, \rho, \tau$ - statistical calibration parameters.

Decision variables:

q_{jk} - O-D traffic flow between centers j and k

w_j - traffic flow in center j

u_l - traffic flow on leg l

v_{jkr} - traffic flow in route r connecting centers j and k

c_{jk} - average travel cost between centers j and k

c_{jkr} - travel cost for route r connecting centers j and k

z_j - final capacity of center j

x_j - congestion tax to apply in center j

y_{jm} - binary variable equal to 1 if expansion action m is applied to center j, and equal to 0 otherwise.

The variables and parameters related with traffic flows on the legs and routes are measured in number of passengers (per day), and the ones related with airport capacities and traffic flows in the centers are defined in enplanements (that is, passenger departures). Travel costs are defined in USD/passenger.

Using the notation above, the mathematical formulation of the model is as follows:

$$\max \sum_{j \in \boldsymbol{N}} w_j \tag{1}$$

subject to:

$$q_{jk} = \alpha \left(p_j p_k \right)^{\mu 1} \left(i_j i_k \right)^{\mu 2} \varphi_{jk}^{\phi} c_{jk}^{-\beta}, \ \forall j,k \in \boldsymbol{N} \tag{2}$$

$$v_{jkr} = \frac{e^{-\gamma c_{jkr}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkp}}} q_{jk}, \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk} \tag{3}$$

$$u_l = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{r \in \boldsymbol{R}_l} v_{jkr} + u_l^*, \ \forall l \in \boldsymbol{L} \tag{4}$$

$$w_j = \sum_{l \in \boldsymbol{L}_j} u_l + w_j^*, \ \forall j \in \boldsymbol{N} \tag{5}$$

$$c_{jkr} = \sum_{l \in \boldsymbol{L}_{jkr}} \sigma \cdot d_l^{\ \nu} \cdot u_l^{\ \varpi} + \sum_{n \in \boldsymbol{N}_{jkr}} \left[\tau + \theta \left(\frac{w_n}{z_n} \right)^{\rho} + x_n \right], \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk} \tag{6}$$

$$c_{jk} = \frac{\sum_{r \in \boldsymbol{R}_{jk}} c_{jkr} v_{jkr}}{q_{jk}}, \ \forall j,k \in \boldsymbol{N} \tag{7}$$

$$z_j \geq w_j, \ \forall j \in \boldsymbol{N} \tag{8}$$

$$z_j = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm} y_{jm}, \ \forall j \in \boldsymbol{N} \tag{9}$$

$$\sum_{m \in \boldsymbol{M}_j} y_{jm} \leq 1, \ \forall j \in \boldsymbol{N} \tag{10}$$

$$\sum_{j \in \boldsymbol{N}} \sum_{m \in \boldsymbol{M}_j} e_{jm} \, y_{jm} \leq b \tag{11}$$

$$y_{jm} \in \{0,1\}, \ \forall j \in \boldsymbol{N}, \ \forall m \in \boldsymbol{M}_j \tag{12}$$

The objective function (1) of the model expresses the maximization of total system throughput, as measured by the total number of enplanements made within the airport network (maximization of “demand coverage”).

Constraints (2) are the O-D demand functions relating the traffic flows between each pair of centers with their population and disposable income per capita, with a modal split factor, and with the average (generalized) travel cost between the centers. The modal split factor was assumed to depend only on travel distance, as follows:

$$\varphi_{jk} = \begin{cases} 0 \Leftarrow d_{jk} < d_{jk\min} \\ \left(\dfrac{d_{jk} - d_{jk\min}}{d_{jk\max} - d_{jk\min}} \right) \Leftarrow d_{jk\min} \leq d_{jk} < d_{jk\max}, \ \forall j,k \in \boldsymbol{N}, \\ 1 \Leftarrow d_{jk} \geq d_{jk\max} \end{cases}$$

where $d_{jk_{min}}$ represents the distance between centers j and k below which no trips are made by air, and $d_{jk_{max}}$ stands for the distance above which all trips are made by air.

Constraints (3) assign the O-D traffic flows to flight routes as a function of the average travel cost through a logit model.

Constraints (4) calculate the traffic flow in each flight leg by summing the traffic flows in the routes containing those legs. These flows may include traffic with origin or destination in airports not included in ***N*** (denoted as u^*).

Constraints (5) compute the enplanements at the centers (airports) by summing the traffic flows in the legs with start point in those centers. These flows may include a traffic with origin, connection or destination in airports not included in ***N*** (denoted as w^*).

Constraints (6) compute the travel cost for each route. This cost is calculated by summing the cost for the legs and the cost for the airports included in that route. The cost for the legs (first term) is assumed to increase with travel distance, and, because of economies of scale, to decrease with traffic flow. The cost for the airports (second term) is assumed to be fixed below a given utilization rate and then to increase because congestion makes airport operations more expensive and time-consuming. The airport cost may include a congestion tax levied by the aviation authority in order to regulate the utilization of airport capacity in case of excess demand.

Constraints (7) calculate the average (generalized) travel cost for each pair of centers by summing the cost for the routes connecting the centers weighted by the respective traffic flow and then dividing by the total traffic flow.

Constraints (8) establish that the airport capacity of the centers must be able to accommodate the traffic flow.

Constraints (9) state that the capacities of the centers are given by the sum of their initial capacities and the capacity increase due to the expansion action applied.

Constraints (10) ensure that at most one expansion action will be applied for each center.

Constraints (11) guarantee that the total expenditure will comply with the budget available for expansion actions.

Finally, constraints (12) define the capacity expansion variables as binary (all other decision variables are non-negative real numbers).

For a detailed explanation of the model formulation, the reader is referred to Chapter 2.

The model formulated above is a complex mixed-integer nonlinear optimization model which is very difficult (if not impossible) to solve using exact solution methods. Thus, we have handled it through the heuristic bi-level solution method described in Chapter 3. The upper-level component of the method generates tentative expansion actions to apply to the airport network through an Add+Interchange algorithm (AIA), and the lower-level component simulates the traffic flows and travel costs in the (expanded) network using the method of successive averages (Ortúzar and Willumsen 2011, p. 370). The simulation of the network is carried out along with the computation of the congestion taxes to apply to the airports when their capacities are not enough to accommodate all demand by means of a line search procedure. This is an iterative process in which solutions are generated and evaluated in consecutive iterations. The best solution obtained in each iteration is compared with the best solution obtained in the previous iterations, and if the former is better than the latter it becomes the new best solution. The iterative process stops when the best solution ceases to improve. AIA was selected to generate the tentative expansion actions as it was shown to provide good solutions within reasonable computation effort. The outline of the solution algorithm is shown in Figure 17. For a detailed explanation of the solution method, the reader is referred to Chapter 3.

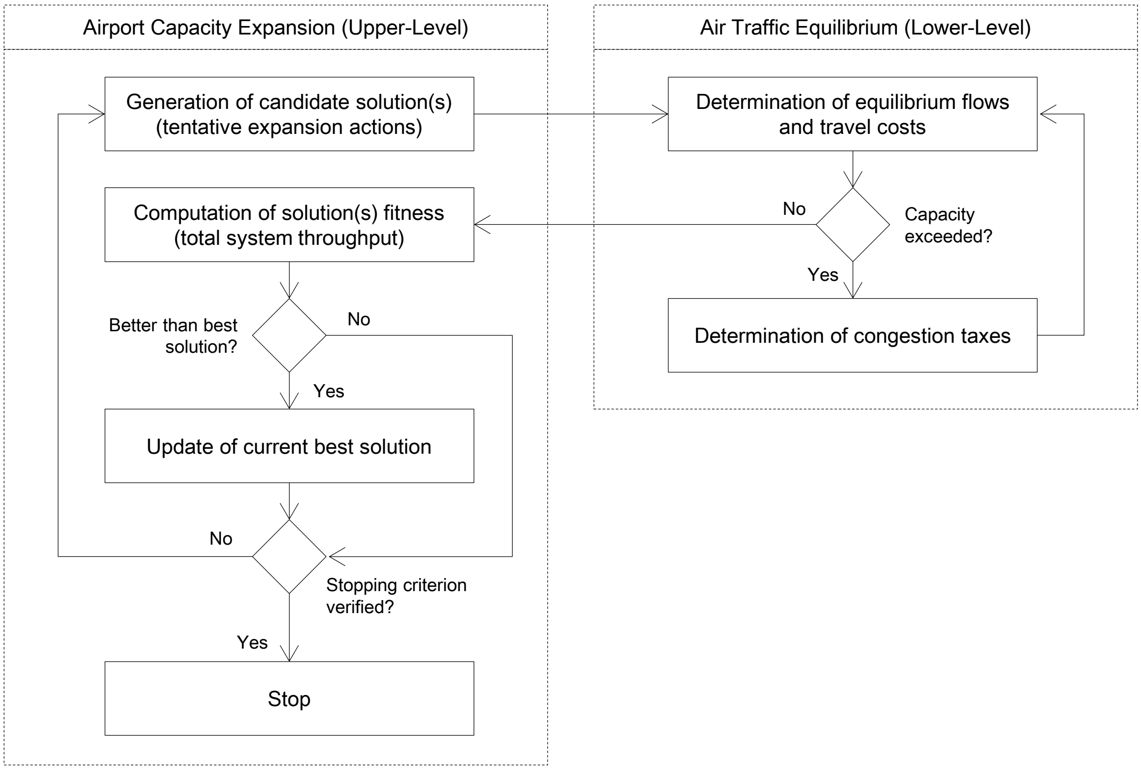


Figure 17 – Outline of the solution algorithm

3. Model calibration

As stated in the previous section, the optimization model embodies a model that simulates the traffic flows and travel costs in the airport network considering the (expanded) capacities of the airports. This simulation model encompasses 11 statistical calibration parameters (α, μ, φ, β, γ, υ, ϖ, θ, ρ, σ, and τ). This section presents the approach we have adopted to calibrate these parameters, as well as the data used and the results obtained through the calibration.

3.1 Calibration approach

The approach used to calibrate the simulation model (embodied in the optimization model) consisted in finding values for the statistical parameters such that the modeled traffic flows (u_l) matched the traffic flows observed (u_l^{obs}) within the airport network. Specifically, we looked for the values of parameters that solve the following optimization model:

$$\min \sum_{l \in \boldsymbol{L}} \left(\frac{u_l - u_l^{obs}}{u_l^{obs}} \right)^2 - G \left(\sum_{j \in \boldsymbol{N}} w_j - \sum_{j \in \boldsymbol{N}} w_j^{obs} \right) \tag{13}$$

subject to:

Constraints (2) – (8)

$$z_j = s_j, \ \forall j \in \boldsymbol{N} \tag{14}$$

The objective function (13) of this model expresses the minimization of the sum of the relative quadratic deviations between modeled and observed traffic flows on the flight legs, plus a penalty dependent on the difference between the total modeled flows and the total observed flows (*G* denotes a number large enough to penalize parameter values which lead to modeled flows different from the observed ones), and constraints (2) to (8) and (14) simulate the traffic flows and travel costs in the network for given airport capacities.

For solving this optimization model, we used the Nelder-Mead algorithm, considered to be one of the most sophisticated global optimization algorithms (Nelder and Mead 1965, Powell 1973, Conn et. al 2009). This algorithm works with a population of solutions, each one corresponding to a given combination of values for the parameters. Let the population of solutions be represented by $POP = \{\lambda_1, \ldots, \lambda_j, \ldots, \lambda_{dim}\}$, where λ_j represents solution *j*, and *dim* represents the size of the population. The initial population of solutions is randomly generated within a given range for each parameter – for all solutions *j* and parameters *k*, $\lambda^{k\_min} < \lambda^k_j < \lambda^{k\_max}$, where λ^{k_min} and λ^{k_max} represent, respectively, the minimum and maximum values for parameter *k* in the initial population. For each solution generated, the network is simulated according to equations (2) to (8), and the value (*fitness*) of the solution is computed through the objective-function (13). Then, in consecutive iterations, the population evolves toward better solutions through the application of four procedures: reflection, expansion, contraction, and shrinkage. The process is repeated for a given maximum number of iterations with no improvement in the best solution. If the best solution improved throughout the iterative process, the initial range for the parameters (as defined by λ^{k_min} and λ^{k_max}) is centered in the best values and the iterative process is repeated; otherwise, the algorithm stops. The pseudo-code of the Nelder-Mead algorithm is shown in Figure 25 of Appendix A.

The Nelder-Mead algorithm uses parameters to guide the search – α^R, α^E, α^{OC}, α^{IC}, and α^S –, which may be estimated through trial-and-error. Alternatively, we have used in our study the values recommended in Conn et al. (2009), which are said to have provided good results in a wide variety of applications. These values are: $\alpha^R = 1$, $\alpha^E = 2$, $\alpha^{OC} = 0.5$, $\alpha^{IC} = -0.5$, and $\alpha^S = 0.5$.

3.2 Calibration data

The simulation model was calibrated using three types of data: (1) socio-economic data for the metropolitan areas; (2) traffic data for the trips made within the airport network; and (3) capacity data for the airports. All data were obtained for the average day of operations in the first quarter of 2008, which was the most recent data available at the time the study was initiated.

3.2.1 Socio-economic data

The population and disposable income per capita of the metropolitan areas were obtained from the Bureau of Economic Analysis, Regional Economic Accounts section (BEA 2010). The population of the metropolitan areas was calculated by summing the population of the counties located within the catchment area of the airports serving the metropolitan areas – it was assumed that a county is included in the catchment area of an airport if its main town is located within one hour’s drive from the airport. The disposable income per capita of the metropolitan areas was calculated by weighting the disposable income per capita of the counties located within the airports catchment area by their population. The Bureau of Economic Analysis provides data on income per capita at the county and state level, and on disposable income per capita at the state level. The disposable income per capita of the counties was calculated assuming that the relation between income per capita for the states and for the counties, obtained through linear regression, holds for the disposable income per capita. The values obtained for the population and disposable income per capita of the metropolitan areas are given in Table 21

3.2.2 Air traffic data

The total traffic flows per leg were obtained from the Air Carrier Statistics T-100 (USDOT-BTS 2012a). The traffic flows with origin, destination, and connection in the airports included in the network were obtained from the Origin and Destination Survey DB1BMarket (USDOT-BTS 2012b), which is a 10% survey that includes trip details such as the operating carrier, origin, connecting, and destination airports, and number of passengers. For the purpose of our study, only non-stop and one-stop routes were considered. The remaining traffic flows (which were used to compute u^* and w^*) are the traffic flows with origin, destination, or connection in airports not included in the network.

Table 21 – Population and disposable income per capita of the metropolitan areas

Metropolitan Area	Population (10^3 inhabitants)	Disposable income per capita (10^3 USD/inhabitant)
Atlanta	5386	28.1
Boston	5704	37.8
Washington	6301	33.2
Cleveland	2094	29.4
Charlotte	1706	29.0
Cincinnati	2159	28.6
Denver	2793	34.4
Dallas	6301	30.5
Detroit	4424	28.6
New York	21380	40.2
Miami	5502	31.5
Houston	5727	33.5
Las Vegas	1879	29.2
Los Angeles	16612	32.4
Orlando	2558	25.7
Chicago	9516	33.2
Memphis	1299	28.3
Minneapolis	3238	34.8
Portland	2204	29.2
Philadelphia	5940	33.6
Phoenix	4287	26.5
Pittsburgh	2355	30.8
San Diego	3019	34.1
Seattle	3842	36.1
San Francisco	6016	44.9
Salt Lake	1112	28.0
Saint Louis	2819	30.6
Tampa	3257	29.1

3.2.3 Airport capacity data

The capacity of the airports in enplanements was obtained by dividing the capacity in movements (aircraft arrivals and departures) by two and multiplying the result with the average number of passengers per movement. In the case of metropolitan areas with more than one airport, we then added the capacity of the different airports. The capacity of the airports in movements (i.e. the maximum number of aircraft that can land or take off throughout the day, by convention defined to be the period between 8 a.m. and 22 p.m.) were taken to be the average daily runway capacities during the first three months of 2008, obtained from FAA's Aviation System Performance Metrics (FAA 2012a, ASQP). The average number of passengers per movement for each metropolitan area was calculated by dividing the total number of passengers (departures and arrivals) by the total number of movements. Table 22 presents the daily capacity for the airports in number of movements, the average number of passengers per movement, and the airport capacity of the metropolitan areas in enplanements.

3.3 Calibration results

The values obtained for the calibration parameters, as well as their initial ranges, are presented in Table 23. The traffic flows simulated with these parameter values and the observed traffic flows are compared in Figure 18, Figure 19 and Figure 20, respectively for the flight legs, the metropolitan areas, and the flight routes. The correlation coefficients between observed and modeled traffic flows for the legs, metropolitan areas, and routes are 0.52, 0.63, and 0.74, respectively. These results show that, overall, our model represents the traffic flows within the airport network in a quite satisfactory manner. Furthermore, the relative deviation between observed and modeled traffic flows at the leg level is less than 25% in 34.5% of the cases, and less than 50% in 66.2% of the cases. For 8.5% of the legs, the model provides an error greater than 100%. The relative deviation for the metropolitan areas is less than 25% and 50% in

50.0% and 60.7% of the cases, respectively, and greater than 100% in 17.9% of the cases. The model also predicts correctly 87.5% of the legs and 98.6% of the routes (a leg/route is said to be correctly predicted if the model sets traffic flow to zero if the leg/route is not operated, and sets traffic flow to a non-zero value otherwise).

4. Network Evolution

In this section, we analyze the long-term evolution of the main US airport network. Specifically, we compare the performance of the airport network for the 10th peak day of operations in 2008 ("current network") with the expected performance of the airport network for an equivalent day in 2030 depending on the budget applied in expansion actions ("future network"). The future network was calculated to maximize system throughput through the optimization model presented earlier in this chapter, and then assessed in the light of the proposals made in the FACT 2 study (FAA 2007). The time required to solve the model for the most demanding instance (the one corresponding to the largest budget) was 5.7 hours. Given the strategic nature of the model, this is not an impracticable computational effort.

In the following sub-sections we discuss the performance of the current network, describe the possible expansion actions applicable to the metropolitan areas and respective costs, and assess the performance of the future network as a function of the budget available.

Table 22– Airport capacities and traffic flows in the metropolitan areas

Metropolitan area	Airport	Average capacity (mov/day)	Average traffic (mov/day)	Average traffic (pax/day)	Average pax/movement	Average capacity (enplanements/day)	
Atlanta	ATL	3174	2411	226610	94	149166	149166
Boston	BOS	1374	817	86484	75	51847	114725
	PVD	810	178			30567	
	MHT	856	151			32310	
Washington	BWI	1148	627	157898	71	40687	142117
	DCA	1029	688			36480	
	IAD	1832	912			64950	
Cleveland	CLE	1265	568	31332	55	34882	56946
	CAK	800	-			22064	
Charlotte	CLT	1923	1259	91062	72	69525	69525
Cincinnati	CVG	3035	778	37084	48	72345	72345
Denver	DEN	3551	1587	129506	82	144882	144882
Dallas	DFW	3007	1620	169430	81	121697	159940
	DAL	945	474			38243	
Detroit	DTW	2403	1157	96090	83	99747	132954
	FNT	800	-			33207	
New York	EWR	1267	968	276588	94	59393	212582
	JFK	1239	968			58069	
	LGA	1120	926			52472	
	ISP	910	90			42648	
Miami	FLL	1189	777	165078	96	56995	149642
	MIA	1932	944			92647	
Houston	IAH	2269	1499	137024	69	78712	105097
	HOU	761	476			26385	
Las Vegas	LAS	1573	1169	121506	104	81741	81741
Los Angeles	LAX	2304	1448	221014	87	100562	271803
	SNA	734	403			32036	
	ONT	1338	277			58399	
	BUR	1096	252			47853	
	LGB	755	152			32954	
Orlando	MCO	2410	942	109506	116	140040	233016
	SFB	1600	-			92976	
Chicago	MDW	950	612	218586	81	38537	142554
	ORD	2563	2081			104017	
Memphis	MEM	2085	759	28870	38	39645	39645
Minneapolis	MSP	2174	1108	92054	83	90262	90262
Portland	PDX	1419	566	36764	65	46083	46083
Philadelphia	PHL	1458	1105	83202	75	54900	85016
	ACY	800	-			30116	
Phoenix	PHX	2006	1266	116258	92	92141	92141
Pittsburgh	PIT	2140	394	22866	58	62105	62105
San Diego	SAN	716	546	48930	90	32082	32082
Seattle	SEA	1280	765	78944	103	66077	66077
San Francisco	SFO	1369	864	148166	84	57254	135471
	OAK	1870	499			78217	
	SJC	1268	409			53061	
Salt Lake	SLC	1964	956	58288	61	59855	59855
Saint Louis	STL	1652	609	37056	61	50244	50244
Tampa	TPA	1616	628	63466	101	81645	162479
	SRQ	800	-			40417	
	PIE	800	-			40417	

Table 23– Initial range and value of the parameters

λ	λ^{min}	λ^{max}	Value
α	0.001	0.01	0.002
$\mu 1$	1	1.5	0.963
$\mu 2$	1	1.5	0.939
ϕ	0	1	0.189
d_{min}	0	1	0.286
d_{max}	1	2	0.812
β	1	2	1.652
σ	200	300	208.72
ν	0	1	0.40
ω	-0.2	0	-0.056
θ	0.01	0.1	0.017
σ	-1	0	-0.50
ρ	1	3	1.813
τ	0	30	22.65
γ	0.01	0.05	0.03

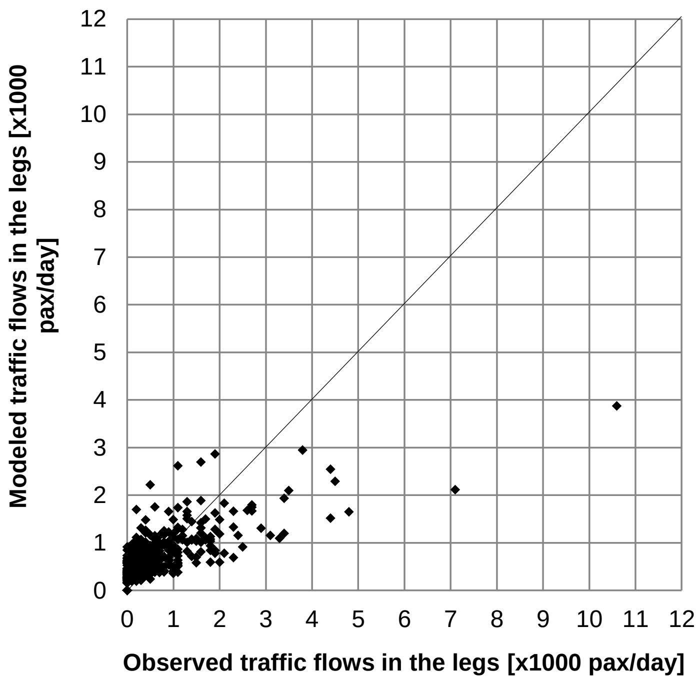


Figure 18– Modeled vs. observed traffic flows in flight legs

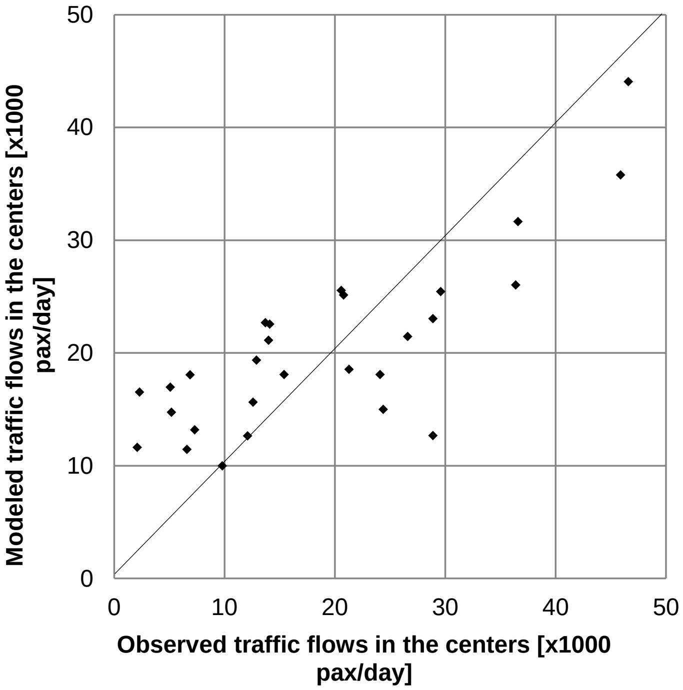


Figure 19– Modeled vs. observed traffic flows in the metropolitan areas

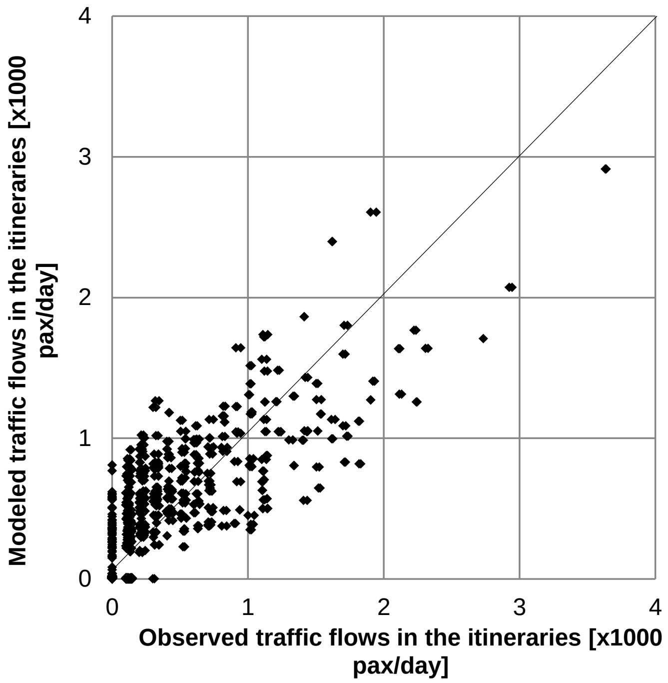


Figure 20– Modeled vs. observed traffic flows in flight routes

4.1 Current network

As stated above, the performance of the current network was analyzed for the 10th peak day of operations of 2008. Since the statistical calibration of model parameters was carried out using data for the average day of operations in 2008, the demand function for trips with a given origin airport, *j*, was multiplied by a peaking factor τ_j (>1). This factor was calculated by dividing the number of movements in the 10th busiest day of the year by the average daily number of movements in the year (the peaking factor for a multi-airport system was assumed to be equal to the peaking factor for the busiest airport in the system), and then adjusted the result to reflect the difference between the average daily number of movements during the year and the average daily number of movements for the first three months of the year, which was the period considered for calibrating the model.

Using the simulation model embedded in the optimization model for the 10th peak day of operations in 2008, we obtained a total number of daily enplanements of $1{,}794\times10^3$ and the traffic pattern represented in Figure 21. The corresponding traffic flows in the metropolitan areas and airport costs (given by the second term of constraints 6) are given in Table 24. All metropolitan areas have enough capacity to satisfy demand, but the utilization rate for the airports in Atlanta, Charlotte, Houston, Chicago, and San Diego is near to or greater than 80%, which is a value commonly assumed to indicate the occurrence of significant airport congestion problems (de Neufville and Odoni 2003).

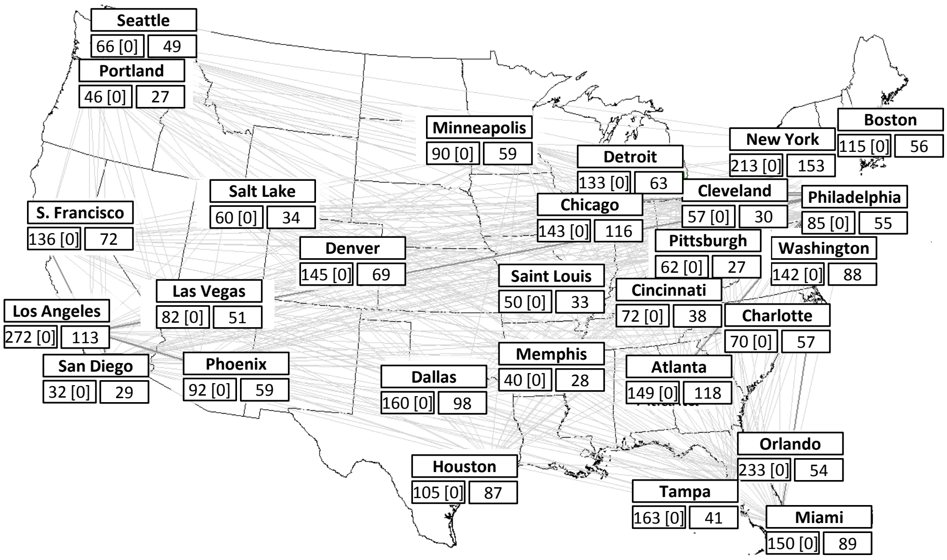


Figure 21– Current airport network

Table 24– Model results for the current network

Metropolitan area	Capacity (10^3 enpl/day)	Traffic (10^3 enpl/day)	Utilization rate (%)	Congestion tax (USD/pax)	Airport costs (USD/pax)
Atlanta	149	118	79	0.00	69.34
Boston	115	56	49	0.00	42.37
Washington	142	88	62	0.00	52.77
Cleveland	57	30	52	0.00	44.55
Charlotte	70	57	82	0.00	73.24
Cincinnati	72	38	53	0.00	45.19
Denver	145	69	48	0.00	41.44
Dallas	160	98	62	0.00	52.47
Detroit	133	63	48	0.00	41.42
New York	213	153	72	0.00	62.37
Miami	150	89	59	0.00	50.55
Houston	105	87	83	0.00	73.44
Las Vegas	82	51	62	0.00	52.90
Los Angeles	272	113	42	0.00	37.35
Orlando	233	54	23	0.00	27.72
Chicago	143	116	81	0.00	72.25
Memphis	40	28	70	0.00	60.54
Minneapolis	90	59	65	0.00	55.79
Portland	46	27	59	0.00	50.71
Philadelphia	85	55	65	0.00	55.84
Phoenix	92	59	64	0.00	54.83
Pittsburgh	62	27	43	0.00	38.24
San Diego	32	29	90	0.00	81.87
Seattle	66	49	74	0.00	64.01
San Francisco	136	72	53	0.00	45.36
Salt Lake City	60	34	57	0.00	48.95
Saint Louis	50	33	67	0.00	57.12
Tampa	163	41	25	0.00	28.66

4.2 Expansion Actions

The possible expansion actions to apply to the metropolitan areas were assumed to consist of the addition or reconfiguration of runways, as runways are generally the most constraining elements of an airport. The following rules were considered: (i) the addition of runways to the existing airports is made so as to coincide with the prevailing wind direction (which was assumed to be the direction of the majority of the existing runways); (ii) the addition of an independent runway to the existing runway layout increases capacity by 400 aircraft departures per day; (iii) the addition of a close parallel runway or a medium-spaced parallel runway to an independent runway increases capacity by 200 and 300 departures per day, respectively; (iv) a new airport can be built in all metropolitan areas, thus making it possible to overcome the difficulty of expanding existing airports often located in consolidated urban areas. It is worth noting here that the capacity increase values indicated above are not intended to match the specific conditions of each airport; they are hypothetical figures based on real expansion projects.

Take for example the Charlotte metropolitan area, which is only served by the Charlotte Douglas International (CLT) airport (Figure 26 in Appendix B). It was assumed that the CLT airport can be expanded through the addition of one or two close parallel runways, increasing capacity by 200 and 400 departures per day, respectively (medium-spaced parallel runways were not considered given space limitations). In addition to the expansion of the CLT airport, it was assumed that it is possible to increase the capacity of the Charlotte metropolitan area through the construction of a new airport. The new airport can have one runway (capacity of 400 departures per day as it is an independent runway), to which can be added a close parallel runway, a medium-spaced parallel runway, or an independent runway (increasing capacity by 200, 300 or 400 departures per day, respectively). Table 31 of Appendix B presents the possible expansion actions applicable to the metropolitan areas and corresponding capacity increases.

The airport capacity increases (in enplanements per day) corresponding to the possible expansion actions applicable to the metropolitan areas are shown in Table 25. The cost of the capacity increases, which were obtained assuming that the construction of a new single runway airport costs 8 billion USD, and the addition of a close-parallel runway, a medium-spaced parallel runway, and an independent parallel runway, costs, respectively, 2, 4 and 6 billion USD, are presented in Table 26.

4.3 Future Network

The future network was obtained through the optimization model for the 10th peak day of operations in 2030 as a function of three budget values: b=0 (no expansion budget), b=100 billion USD, and b=200 billion USD. The demand to satisfy was defined assuming that population and disposable income will continue to evolve in the various metropolitan areas according to the same patterns as between 1998 and 2008 (the disposable income per capita was converted to constant 2005 USD using the Implicit Price Deflators for GDP provided by the Bureau of Economic Analysis). The traffic flows with origin, destination or connection in airports not included in the network (u*

Table 25 – Possible airport capacity increases in the metropolitan areas (10^3 enplanements/day)

Metro. Area	Expansion level										
	1	2	3	4	5	6	7	8	9	10	…
Atlanta	**38**	**56**	**66**	**75**	**94**	**113**	-	-	-	-	-
Boston	15	23	38	**68**	**83**	**91**	**98**	**113**	**129**	-	-
Washington	14	21	35	49	63	**91**	**106**	**113**	**120**	**134**	**148**
Cleveland	22	33	39	**61**	**72**	**78**	**83**	**94**	**105**	-	-
Charlotte	14	29	**58**	**72**	**80**	**87**	**101**	**116**	-	-	-
Cincinnati	10	19	**38**	**48**	**52**	**57**	**67**	**76**	-	-	-
Denver	33	49	**82**	**98**	**106**	**114**	**131**	**147**	-	-	-
Dallas	16	**48**	**65**	**73**	**81**	**97**	**113**	-	-	-	-
Detroit	17	**50**	**67**	**75**	**83**	**100**	**117**	-	-	-	-
New York	**37**	**56**	**66**	**75**	**94**	**112**	-	-	-	-	-
Miami	**38**	**58**	**67**	**77**	**96**	**115**	-	-	-	-	-
Houston	14	42	**70**	**84**	**91**	**98**	**112**	**126**	-	-	-
Las Vegas	**42**	**62**	**73**	**83**	**104**	**125**	-	-	-	-	-
Los Angeles	**35**	**52**	**61**	**70**	**87**	**105**	-	-	-	-	-
Orlando	23	46	58	81	**127**	**151**	**162**	**174**	**197**	**220**	-
Chicago	**32**	**49**	**57**	**65**	**81**	**97**	-	-	-	-	-
Memphis	8	**23**	**31**	**35**	**38**	**46**	**54**	-	-	-	-
Minneapolis	17	**50**	**67**	**75**	**83**	**100**	**117**	-	-	-	-
Portland	13	**39**	**52**	**58**	**65**	**78**	**91**	-	-	-	-
Philadelphia	15	30	38	**68**	**83**	**91**	**98**	**113**	**128**	-	-
Phoenix	18	**55**	**73**	**82**	**91**	**110**	**128**	-	-	-	-
Pittsburgh	12	**35**	**47**	**53**	**58**	**70**	**82**	-	-	-	-
San Diego	**36**	**54**	**63**	**72**	**90**	**108**	-	-	-	-	-
Seattle	21	**62**	**83**	**93**	**104**	**124**	**145**	-	-	-	-
San Francisco	17	25	**58**	**75**	**84**	**92**	**109**	**125**	-	-	-
Salt Lake City	12	**36**	**49**	**55**	**61**	**73**	**85**	-	-	-	-
Saint Louis	12	**36**	**49**	**55**	**61**	**73**	**85**	-	-	-	-
Tampa	20	40	60	**100**	**121**	**131**	**141**	**161**	**181**	-	-

Note: capacity increases marked in bold require construction of new airport

Table 26– Cost of airport capacity increases (bio USD)

Metro. Area	Expansion level										
	1	2	3	4	5	6	7	8	9	10	…
Atlanta	8	10	12	14	16	18	-	-	-	-	-
Boston	6	8	14	22	24	26	28	30	32	-	-
Washington	6	8	14	23	26	34	36	38	40	42	44
Cleveland	9	15	17	25	27	29	31	33	35	-	-
Charlotte	6	8	16	18	20	22	24	26	-	-	-
Cincinnati	6	8	16	18	20	22	24	26	-	-	-
Denver	9	12	20	22	24	26	28	30	-	-	-
Dallas	6	14	16	18	20	22	24	-	-	-	-
Detroit	6	14	16	18	20	22	24	-	-	-	-
New York	8	10	12	14	16	18	-	-	-	-	-
Miami	8	10	12	14	16	18	-	-	-	-	-
Houston	6	15	23	25	27	29	31	33	-	-	-
Las Vegas	8	10	12	14	16	18	-	-	-	-	-
Los Angeles	8	10	12	14	16	18	-	-	-	-	-
Orlando	6	9	12	14	22	24	26	28	30	32	-
Chicago	8	10	12	14	16	18	-	-	-	-	-
Memphis	5	13	15	17	19	21	23	-	-	-	-
Minneapolis	6	14	16	18	20	22	24	-	-	-	-
Portland	6	14	16	18	20	22	24	-	-	-	-
Philadelphia	6	6	8	16	18	20	22	24	26	-	-
Phoenix	5	13	15	17	19	21	23	-	-	-	-
Pittsburgh	5	13	15	17	19	21	23	-	-	-	-
San Diego	8	10	12	14	16	18	-	-	-	-	-
Seattle	5	13	15	17	19	21	23	-	-	-	-
San Francisco	9	12	20	22	24	26	28	30	-	-	-
Salt Lake City	5	13	15	17	19	21	23	-	-	-	-
Saint Louis	5	13	15	17	19	21	23	-	-	-	-
Tampa	6	12	18	26	28	30	32	34	36	-	-

and *w**) were considered to increase by 2.8% per year for all flight legs and airports, which is consistent with the projections of FAA (FAA 2011a).

4.3.1 No Expansion Budget

For the demand scenario considered (same demand function as in 2008, with the population and disposable income forecast for 2030), and assuming that the airport network would remain the same (b=0), 10 metropolitan areas would suffer from severe lack of capacity (and the utilization rate of another 9 would exceed 80%). For the five metropolitan areas that already exhibited congestion problems in 2008, a minimum of 151.0 USD would have to be charged per passenger in order to regulate the utilization of capacity (avoiding excess demand situations). New York, Las Vegas, Memphis, Phoenix and Seattle would also run out of capacity, and a congestion tax ranging between 5.6 and 82.9 USD should be applied there to each passenger. In Washington, Dallas, Miami, Minneapolis and Philadelphia, capacity would virtually match demand, but no congestion taxes would need to be charged. The number of daily enplanements in the network would rise to $2{,}600\times10^3$, corresponding to an increase of about 45% relative to the current network.

4.3.2 Expansion budget of 100 billions USD

If a budget of 100 billion USD were applied toward the expansion of the existing airport network, the best option (according to the optimization model) would be to increase capacity in eleven metropolitan areas: airports in Las Vegas, Seattle, San Diego, Phoenix, Dallas and Minneapolis should be expanded one level (a new single-runway

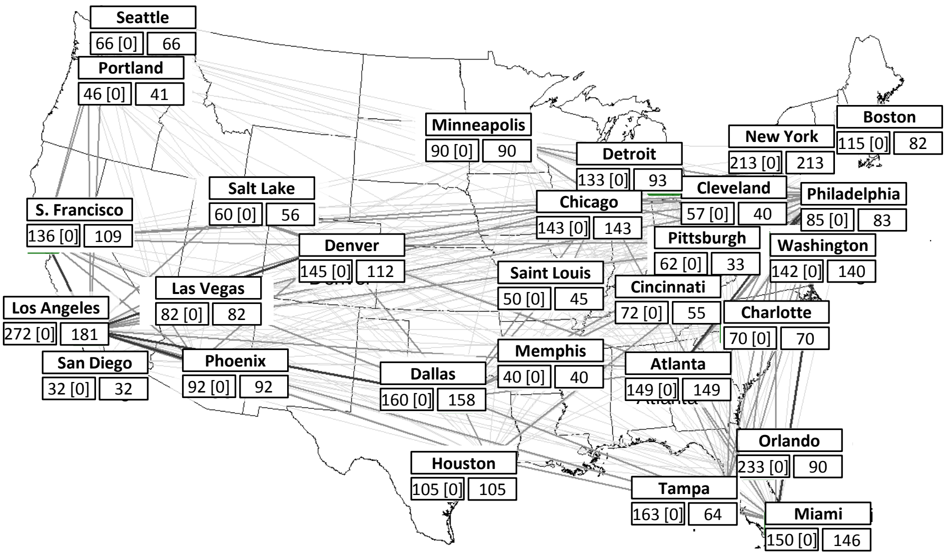


Figure 22 – Future airport network (*b*=0)

Table 27– Model results for the current network (*b*=0)

Metropolitan area	Capacity (10^3 enpl/day)	Traffic (10^3 enpl/day)	Utilization rate (%)	Congestion tax (USD/pax)	Airport costs (USD/pax)
Atlanta	149	149	100	197.47	94.62
Boston	115	82	71	0.00	61.57
Washington	142	140	99	0.00	92.77
Cleveland	57	40	70	0.00	59.95
Charlotte	70	70	100	227.27	94.62
Cincinnati	72	55	77	0.00	66.99
Denver	145	112	77	0.00	67.88
Dallas	160	158	99	0.00	93.41
Detroit	133	93	70	0.00	59.96
New York	213	213	100	51.64	94.63
Miami	150	146	98	0.00	91.51
Houston	105	105	100	198.58	94.63
Las Vegas	82	82	100	12.21	94.63
Los Angeles	272	181	67	0.00	57.03
Orlando	233	90	39	0.00	35.48
Chicago	143	143	100	151.20	94.63
Memphis	40	40	100	5.59	94.64
Minneapolis	90	90	99	0.00	93.95
Portland	46	41	90	0.00	81.76
Philadelphia	85	83	98	0.00	91.96
Phoenix	92	92	100	12.50	94.63
Pittsburgh	62	33	54	0.00	46.05
San Diego	32	32	100	184.84	94.64
Seattle	66	66	100	82.88	94.63
San Francisco	136	109	81	0.00	71.29
Salt Lake City	60	56	93	0.00	85.68
Saint Louis	50	45	90	0.00	82.59
Tampa	163	64	39	0.00	35.85

airport should be built in Las Vegas and Seattle); in New York, Chicago, Charlotte and Atlanta should be expanded two levels (a new airport with two close-parallel runways should be built in New York, Chicago and Atlanta); and in Houston should be expanded three levels (a new runway should be added to Houston Intercontinental/IAH and to Houston Hobby/HOU, and a new single-runway airport should be built). These metropolitan areas would then have enough capacity to serve all demand. On the other hand, for the cases of Washington, Memphis and Philadelphia, which should not be expanded, congestion taxes of 6.7, 31.3 and 4.4 USD, respectively, would have to be charged to each passenger in order to regulate the utilization of capacity. The total number of daily enplanements would rise to $2{,}930 \times 10^3$, which corresponds to an increase of 64% relative to the current network, and 12% relative to the "no expansion" budget solution.

4.3.3 Expansion budget of 200 billions USD

With a budget of 200 billion USD, the airport network should be further improved as follows: the airport capacity in Los Angeles, Denver, St. Louis and Washington should be expanded one level (a new single-runway airport should be built in Los Angeles); in Seattle, San Diego, Phoenix, Minneapolis, Dallas, Memphis, Miami and Philadelphia should be expanded two levels (a single-runway airport should be built in Seattle, Phoenix, Minneapolis, Dallas and Memphis, and an airport with two close-parallel runways should be built in Miami and San Diego); and in Chicago and Charlotte should be expanded three levels (a new single-runway airport should be built in Charlotte, and

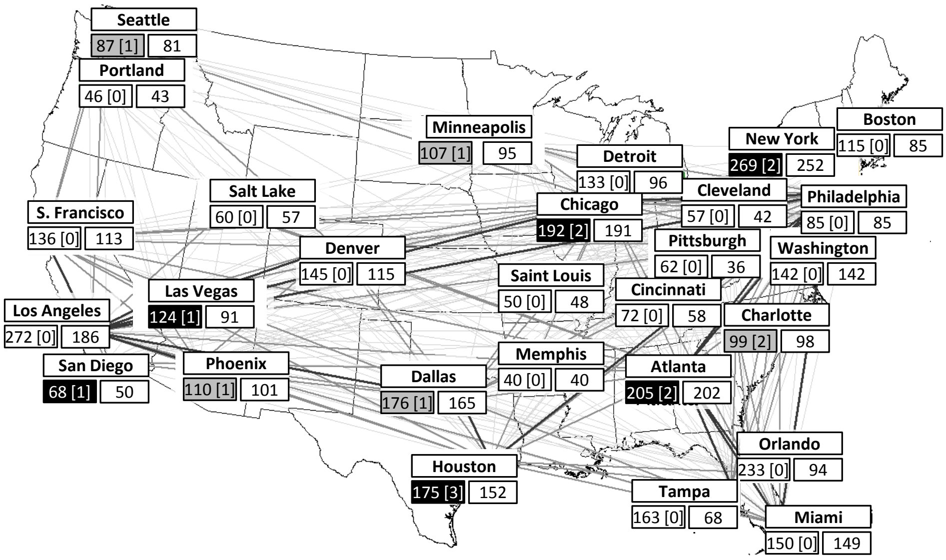


Figure 23 – Future airport network (*b*=100 bio USD)

Table 28 – Future airport network (*b*=100 bio USD)

Metropolitan area	Capacity (10^3 enpl/day)	Traffic (10^3 enpl/day)	Utilization rate (%)	Congestion tax (USD/pax)	Airport costs (USD/pax)
Atlanta	205	202	98	0.00	92.29
Boston	115	85	74	0.00	64.68
Washington	142	142	100	6.74	94.62
Cleveland	57	42	73	0.00	63.63
Charlotte	99	98	100	0.00	94.20
Cincinnati	72	58	80	0.00	70.42
Denver	145	115	80	0.00	70.16
Dallas	176	165	94	0.00	86.74
Detroit	133	96	72	0.00	62.26
New York	269	252	94	0.00	86.84
Miami	150	149	100	0.00	94.44
Houston	175	152	87	0.00	78.38
Las Vegas	124	91	73	0.00	63.59
Los Angeles	272	186	68	0.00	58.85
Orlando	233	94	40	0.00	36.42
Chicago	192	191	100	0.00	94.30
Memphis	40	40	100	31.27	94.62
Minneapolis	107	95	89	0.00	80.90
Portland	46	43	93	0.00	85.20
Philadelphia	85	85	100	4.41	94.62
Phoenix	110	101	92	0.00	84.13
Pittsburgh	62	36	58	0.00	49.52
San Diego	68	50	74	0.00	64.13
Seattle	87	81	93	0.00	86.02
San Francisco	136	113	84	0.00	74.56
Salt Lake City	60	57	95	0.00	88.74
Saint Louis	50	48	95	0.00	88.18
Tampa	163	68	42	0.00	37.42

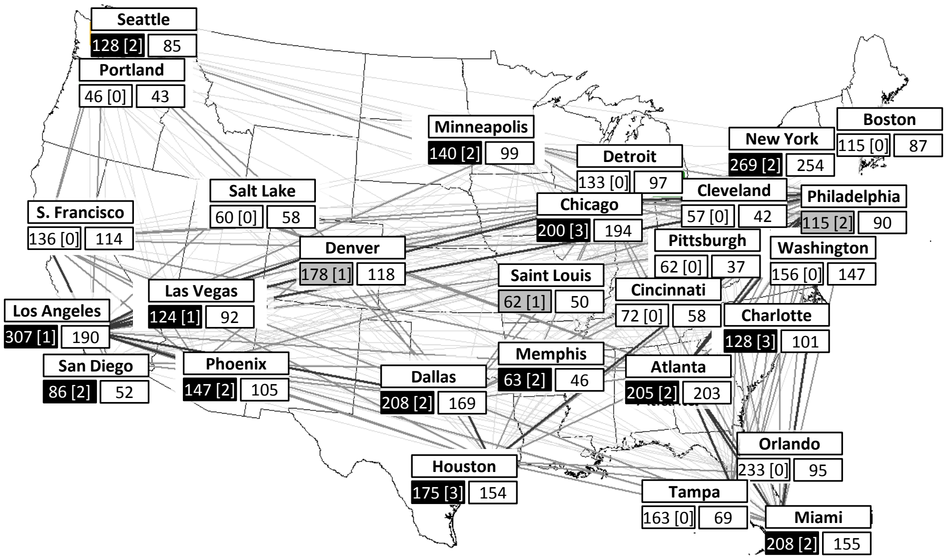


Figure 24 – Future airport network (*b*=200 bio USD)

Table 29– Model results for the current network (*b*=200 bio USD)

Metropolitan area	Capacity (10^3 enpl/day)	Traffic (10^3 enpl/day)	Utilization rate (%)	Congestion tax (USD/pax)	Airport costs (USD/pax)
Atlanta	205	203	99	0.00	93.06
Boston	115	87	75	0.00	65.81
Washington	156	147	94	0.00	86.93
Cleveland	57	42	75	0.00	64.87
Charlotte	128	101	79	0.00	70.10
Cincinnati	72	58	81	0.00	71.61
Denver	178	118	66	0.00	56.85
Dallas	208	169	81	0.00	72.04
Detroit	133	97	73	0.00	63.07
New York	269	254	95	0.00	87.70
Miami	208	155	75	0.00	64.85
Houston	175	154	88	0.00	79.37
Las Vegas	124	92	74	0.00	64.34
Los Angeles	307	190	62	0.00	52.73
Orlando	233	95	41	0.00	36.75
Chicago	200	194	97	0.00	90.70
Memphis	63	46	73	0.00	63.59
Minneapolis	140	99	71	0.00	60.95
Portland	46	43	93	0.00	86.18
Philadelphia	115	90	79	0.00	69.08
Phoenix	147	105	71	0.00	61.81
Pittsburgh	62	37	59	0.00	50.67
San Diego	86	52	61	0.00	51.88
Seattle	128	85	66	0.00	56.81
San Francisco	136	114	84	0.00	75.63
Salt Lake City	60	58	96	0.00	89.76
Saint Louis	62	50	81	0.00	71.82
Tampa	163	69	43%	0.00	37.96

the new airport for Chicago should be upgraded to two medium-spaced parallel runways). With these changes, all metropolitan areas would have enough capacity to satisfy demand without being necessary to apply congestion taxes. The total number of daily enplanements would rise to $3{,}000\times10^3$, which corresponds to an increase of 67% relative to the current network, and 15% relative to the "no expansion" budget solution. It is worth noting here that the additional 100 billion USD would have a very minor impact on the performance of the airport network (an increase of 100% in the budget would lead to an increase of less than 3% in system throughput).

4.4 Comparison with FACT 2 study results

Overall, the results obtained through our study (model results) are quite consistent with the results of the FACT 2 study (FAA 2007). Indeed, as shown in Table 30, the assessment of FAA with respect to airport expansion needs does not match the results of our study only in 4 of the 28 metropolitan areas under consideration: San Diego and Las Vegas are identified by the model as facing airport congestion problems if nothing is done, whereas FAA does not anticipate problems in these areas, and the opposite occurs with Cincinatti and Denver. The differences between the two studies are more significant as regards to investment recommendations. Our study suggests that fewer metropolitan areas require capacity expansion (17 against 19 in the FACT2 study to fully cope with congestion), and there are a number of differences in the metropolitan areas where to improve the airports – the model does not recommend Washington, Cincinnati, Portland, San Francisco, and Salt Lake City for investment, pointing instead to Las Vegas, Los Angeles, and San Diego. One possible explanation is that in our study, and unlike in the study carried out by the FAA, network effects are taken into account. This implies that, by expanding capacity in one metropolitan area, traffic may be diverted from other metropolitan areas, thus alleviating possible congestion problems that may be faced there.

With respect to the results presented above, it is important to emphasize that (a) the FACT2 study was conducted in 2007 and therefore did not consider the decline in demand for air transportation due to the 2008-2009 economic downturn, and (b) its horizon year was 2025. These facts certainly contribute to explain part of the differences between the outcomes of the two studies.

5. Conclusion

This chapter presents the results of a study regarding the long-term evolution of the network of the principal airports in the US. The study was based on the optimization model proposed in Chapter 2 to assist aviation authorities in their strategic decisions regarding the expansion of airport networks. The model is applied to a set of metropolitan areas and determines the expansion actions to apply to their airports (or multi-airport systems) that maximize system throughput while complying with a given national budget.

Table 30– Metropolitan areas needing additional capacity according to the results obtained by the model and according to the FACT 2 study

Metropolitan Area	Areas/airports needing capacity	Areas/airports recommended for investment		
	Model study *b* = 0	FACT 2 study	Model study *b* = 100 bio USD	Model study *b* = 200 bio USD
Atlanta	x	x	x	x
Boston				
Washington	x	x		
Cleveland				
Charlotte	x	x	x	x
Cincinnati		x		
Denver		x		x
Dallas	x	x	x	x
Detroit				
New York	x	x	x	x
Miami	x	x		x
Houston	x	x	x	x
Las Vegas	x		x	x
Los Angeles				x
Orlando				
Chicago	x	x	x	x
Memphis	x	x		x
Minneapolis	x	x	x	x
Portland	x	x		
Philadelphia	x	x		x
Phoenix	x	x	x	x
Pittsburgh				
San Diego	x		x	x
Seattle	x	x	x	x
San Francisco	x	x		
Salt Lake City	x	x		
Saint Louis	x	x		x
Tampa				

The study focused on the airports of 28 metropolitan areas of the US (the metropolitan areas where the 34 OEP airports are located). These airports handle a large share of the total traffic in the US and are connected to many airports, which means that the congestion problems that may affect them propagate through the whole airport network. The horizon year we considered was 2030. The results we obtained with respect to the 10th peak day of operations in that year reveal that, if nothing is done, 10 (out of the 28) metropolitan areas will not have enough capacity to satisfy all demand (and the utilization rate of another 9 will exceed 80%). We have also analyzed the best way of improving the existing airport network with budgets of 100 billion and 200 billion USD. One of the main conclusions of the study was that, in going from a budget of 100 billion to one of 200 billion, the additional 100 billion dollars will have only a minor impact on system throughput. Another important conclusion was that, because of network effects, it is possible to eliminate airport congestion by concentrating investment in fewer metropolitan areas than the ones recommended for capacity expansion in FAA's FACT2 study.

With respect to our results, it must be emphasized here that they are the outcome of a study that adopted a policy-level, macroscopic perspective. Some feasibility issues involved in the expansion of the existing airports were dealt with in a very approximate way. Our purpose was essentially to demonstrate that the optimization model upon which the study is based can be useful to support analyses of the evolution of airport networks and to provide insights into the best way of expanding them. We believe this was successfully accomplished. It must also be emphasized that, similar to the FACT2 study, we did not take into account the impact of NextGEN interventions on the performance of the US airport network. These measures are supposed to lead to substantial capacity increases, thus reducing the need for capacity expansion actions.

In the future, we plan to extend our study to the case where NextGEN measures and capacity expansion actions are carried out in combination to improve the airport network. This will provide interesting information on the benefits that NextGEN measures can generate. Another direction that we intend to pursue relates to the system's dynamic behavior, as well as to uncertainty about future demand. Indeed, our analysis was carried out with respect to a distant future considering only one demand scenario. If several plausible scenarios for demand (and other variables) could be taken into account simultaneously and we could distinguish between short-term actions and medium/long-term ones, the practical relevance of the analysis would certainly be greatly enhanced.

6. Appendix A: pseudo-code of the Nelder Mead Algorithm

INITIALIZATION

1) Generate an initial population of random solutions, POP (λ_1,…,λ_j,…,λ_{dim}), where λ_j denotes the combination of parameters in solution *j*, and *dim* denotes the size of the population
2) *FITNESS* [*fitness*(λ_1),…,*fitness*(λ_j),…,*fitness*(λ_{dim})] ← evaluate (POP)
3) Rank solutions by decreasing value of fitness
4) Set best solution of the initial population as best solution:
    4.1) $\lambda_B \leftarrow \lambda_1$
    4.2) *fitness*(λ_B) ← *fitness*(λ_1)
5) $t \leftarrow 0$

UPDATE OF THE POPULATION

6) $t \leftarrow t+1$
7) Reflection:
    7.1) $\lambda_c \leftarrow$ (1/*dim*).sum(*j* in 1..*dim*) POP_j
    7.2) $\lambda_R \leftarrow \lambda_c + \alpha_R(\lambda_c - POP_{dim})$
    7.3) *if fitness*(λ_R) is not better than fitness(λ_1) but better than fitness(λ_{dim-1}) *then*:
            $\lambda_{dim} \leftarrow \lambda_R$
        else-if fitness(λ_R) is better than *fitness*(λ_1) *then*:
            move to 8) Expansion
        else-if fitness(λ_R) is worse than *fitness*(λ_{dim-1}) but better than *fitness*(λ_{dim}) *then*:
            move to 9) Outside contraction
        else-if fitness(λ_R) is worse than fitness(λ_{dim}) *then*:
            move to 10) Inside contraction
        end-if
8) Expansion:
    8.1) $\lambda_E \leftarrow \lambda_C + \alpha_E(\lambda_C - POP_{dim})$
    8.2) *if fitness*(λ_E) is better than *fitness*(λ_R) *then*
            $\lambda_{dim} \leftarrow \lambda_E$
        else
            $\lambda_{dim} \leftarrow \lambda_R$
        end-if
    8.2) move to 12)
9) Outside contraction:
    9.1) $\lambda_{OC} \leftarrow \lambda_C + \alpha_{OC}(\lambda_C - POP_{dim})$
    9.2) *if fitness*(λ_{OC}) is better than *fitness*(λ_R) *then*
            $\lambda_{dim} \leftarrow \lambda_{OC}$
        else
            move to 11) Shrink
        end-if
    9.3) move to 12)
10) Inside contraction:

```
        10.1)      λIC ← λC + αIC(λC−POPdim)
        10.2)      if fitness(λIC) is better than fitness(λR) then
                        λdim ← λIC
                   else
                        move to 11) Shrink
                   end-if
        10.3)      move to 12)
11) Shrink:
        11.1)      for all solutions j in {2..dim}: λj ← λ1 + αS(λj−λ1)
        11.2)      move to 12)
12) Rank solutions by decreasing value of fitness
13) if fitness(λ1) is better than fitness(λB) then
        λB ← λ1
        fitness(λB) ← fitness(λ1)
        t ←0
    else
        t ← t+1
    end-if
14) if t<tmax then
        move to 6)
    else
        STOP.
    end-if
```

Figure 25 – Pseudo-code of the Nelder-Mead method

7. Appendix B: definition of the admissible expansion actions

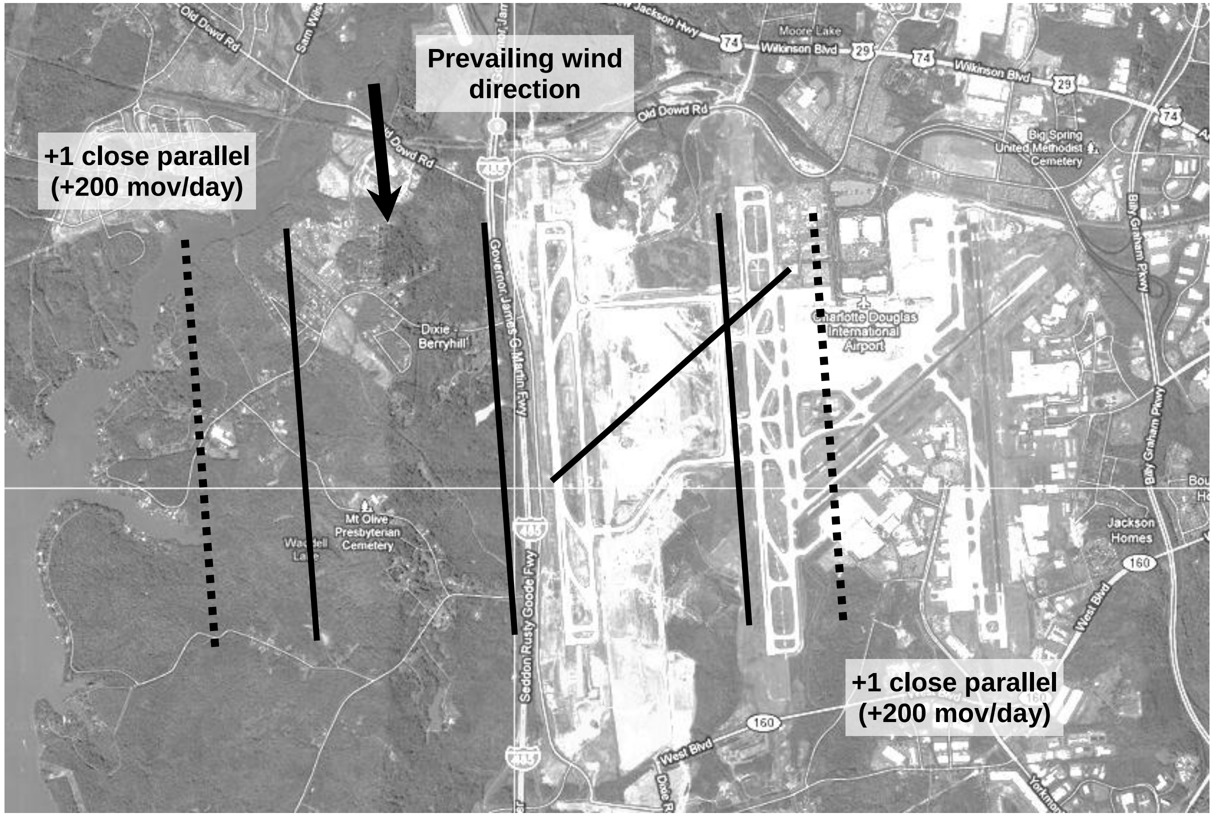
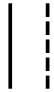
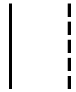
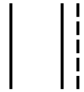
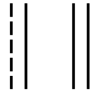


Figure 26 – Definition of the possible expansion actions applicable to Charlotte Douglas International Airport

Table 31 – Expansion actions applicable to the airports and corresponding increase in capacity (values in number of movements per day)

Metro. Area	Airports	+ independent runway	+ close parallel runway	+ medium-spaced parallel runway	+ independent parallel runway	+ close parallel runway	+ close parallel runway
Atlanta	ATL	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Boston	BOS	0	0	0	0	0	0
	PVD	0	200	0	0	0	0
	MHT	0	200	300	0	0	0
	New airport	400	600	700	800	1000	1200
Washington	BWI	0	0	0	200	400	0
	DCA	0	200	0	0	0	0
	IAD	0	200	300	0	0	0
	New airport	400	600	700	800	1000	1200
Cleveland	CLE	0	0	0	400	0	0
	CAK	0	200	300	0	0	0
	New airport	400	600	700	800	1000	1200
Charlotte	CLT	0	0	0	0	200	400
	New airport	400	600	700	800	1000	1200
Cincinnati	CVG	0	0	0	0	200	400
	New airport	400	600	700	800	1000	1200
Denver	DEN	0	0	0	400	600	0
	New airport	400	600	700	800	1000	1200
Dallas	DFW	0	0	0	0	200	0
	DAL	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Detroit	DTW	0	0	0	0	0	0
	FNT	0	200	0	0	0	0
	New airport	400	600	700	800	1000	1200
New York	EWR	0	0	0	0	0	0
	JFK	0	0	0	0	0	0
	LGA	0	0	0	0	0	0
	ISP	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200

Metro. Area	Airports	+ independent runway	+ close parallel runway	+ medium-spaced parallel runway	+ independent parallel runway	+ close parallel runway	+ close parallel runway
Miami	FLL	0	0	0	0	0	0
	MIA	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Houston	IAH	0	0	0	0	200	0
	HOU	0	0	0	400	0	0
	New airport	400	600	700	800	1000	1200
Las Vegas	LAS	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Los Angeles	LAX	0	0	0	0	0	0
	SNA	0	0	0	0	0	0
	ONT	0	0	0	0	0	0
	BUR	0	0	0	0	0	0
	LGB	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Orlando	MCO	0	0	0	0	200	0
	SFB	0	0	0	200	300	500
	New airport	400	600	700	800	1000	1200
Chicago	MDW	0	0	0	0	0	0
	ORD	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Memphis	MEM	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
Minneapolis	MSP	0	0	0	0	200	0
	New airport	400	600	700	800	1000	1200
Portland	PDX	0	0	0	0	200	0
	New airport	400	600	700	800	1000	1200
Philadelphia	PHL	0	0	0	0	200	0
	ACY	0	200	300	0	0	0
	New airport	400	600	700	800	1000	1200

Metro. Area	Airports	+ independent runway	+ close parallel runway 	+ medium-spaced parallel runway 	+ independent parallel runway 	+ close parallel runway 	+ close parallel runway 
Phoenix	PHX	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
Pittsburgh	PIT	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
San Diego	SAN	0	0	0	0	0	0
	TIJ	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Seattle	SEA	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
San Francisco	SFO	0	0	0	0	0	0
	OAK	0	0	0	200	300	0
	SJC	0	0	0	0	0	0
	New airport	400	600	700	800	1000	1200
Salt Lake City	SLC	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
Saint Louis	STL	0	0	0	0	0	200
	New airport	400	600	700	800	1000	1200
Tampa	TPA	0	0	0	0	200	0
	SRQ	0	200	0	0	0	0
	PIE	0	200	0	0	0	0
	New airport	400	600	700	800	1000	1200

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Chapter 5

Insights into the Long-Term Evolution of the Airport Network of Germany

1. Introduction

After the reunification of Germany in 1990, demand for air transportation experienced a significant growth. In terms of passenger traffic, total enplanements increased about 140%, from 79 million in 1991 to 191 million in 2010, corresponding to an average annual rate of 4.8% per year (ADV 2011). Among the reasons which contributed to this growth are the central position of Germany within Europe, which makes it a good hub for international air transport, the enlargement of the European Union to the East in 2004, and the liberalization of the aviation sector in the European Union in 1993 (BMVBS 2003).

Current long-term forecasts indicate that demand for air transportation will continue to increase at a significant pace in the following two decades. According to EUROCONTROL (2010b), the number of aircraft movements will increase by 2.8% per year between 2010 and 2030 ('most-likely' scenario). The projected growth in traffic will lead to the escalation of congestion problems and flight delays at several airports across the country if no actions are taken. ECAD (2010) projects that the airports of Frankfurt am Main (FRA), Frankfurt-Hahn (HHN), München (MUC), Düsseldorf International (DUS), Hamburg-Fuhlsbüttel (HAM), Stuttgart (STR), Köln/Bonn (CGN), Hannover-Langenhagen (HAJ), Nürnberg (NUE), and the Berlin metropolitan area will exhibit congestion problems in 2020.

Airport congestion problems can be dealt with from the demand side, through demand management mechanisms, and from the supply side, through scaling mechanisms (Bonnefoy and Hansman 2008). Demand management mechanisms address the demand/supply imbalance either through regulatory measures (e.g. slot control) or market-based measures (e.g. congestion pricing). Scaling mechanisms improve supply either by augmenting the efficiency of operations (e.g. increase of aircraft size) or by increasing the capacity of airport infrastructures, through the improvement of air traffic management systems, the expansion of existing airports, and the construction of new airports. The improvement of air traffic management systems may accommodate some increase in traffic (as foreseen by FAA's NextGEN Implementation Plan for United States, FAA 2012b). However, in the long term, the expansion of existing airports and the construction of new airports may be necessary to deal with the growing volumes of air traffic and attenuate the escalation of congestion problems.

In Germany, the construction and expansion of airports is mainly ensured by private entities (with possible support from the federal states). However, the central government is responsible for coordinating the expansion projects from a superregional and intermodal perspective (BMVBS 2003). It is, thus, the responsibility of the central government to ensure that the capacity of the airport infrastructure meets the projected levels of demand, and to guarantee that the necessary long-distance transport links are provided by connecting the airports with the rail and road networks.

This chapter describes a study which purpose is to provide some insights into the long-term capacity needs of the main airports in Germany. Unlike other published studies dealing with airport construction and/or expansion problems, this study assesses expansion decisions in the framework of an airport network. The study is based on an optimization model, derived from the one presented in Chapter 2, aimed at assisting aviation authorities in their strategic decisions regarding the expansion of airport networks. The model looks to a set of metropolitan areas, which can either be served by airports/multi-airport systems, or not. The goal of the model is to determine the expansion actions to apply to the metropolitan areas in order to maximize total system throughput for a given budget, taking into account the impact of airport congestion and the complementarity and competition between air travel and land travel modes on travel cost and demand for air transportation. Expansion actions consist of the expansion of existing airports (e.g. through the addition of new runways or the reconfiguration of existing runways) and the construction of new airports.

The chapter is organized as follows. In Section 2, we identify the airports considered in the study. In Section 3, we present the optimization model upon which our results are based and describe the solution method developed to handle it. The type of results that can be expected from the application of the model is then illustrated for a small-size, hypothetical airport network. In Section 4, we explain how the statistical parameters included in the model were calibrated. In Section 5, we present the results obtained by the model. Section 6 summarizes conclusions and identifies directions for further work.

2. Network description

The main airport network of Germany comprises 42 airports, of which 17 are international and 25 are regional (BMVBS, 2003) – in the meanwhile, Berlin-Tegel (TXL) airport will cease operating in 2012 in the process of establishing Berlin-Schönefeld (SXF) as the sole commercial airport for Berlin, Berlin-Brandenburg (BER) (Berlin-Tempelhof THF was also closed in 2008).

In 2009, the international airports handled a traffic volume of almost 171 million passengers (DESTATIS, 2009). The busiest airport was Frankfurt am Main (FRA), serving more than 50 million passengers (see Figure 27), of which around 60% belonged to the home carrier Lufthansa. Due to capacity problems at Frankfurt am Main airport, Lufthansa has transferred a growing part of its hub operations to München airport (MUC), the second busiest airport in Germany. As a consequence, traffic volume at the München airport increased by about 43% from 2002 to 2009 (traffic volume at Frankfurt am Main airport stayed constant in this period, increasing around 4%). Düsseldorf airport (DUS) ranked third, serving about 17.7 million passengers, and the metropolitan area of Berlin handled around 21 million passengers across Berlin-Tegel and Schönefeld.

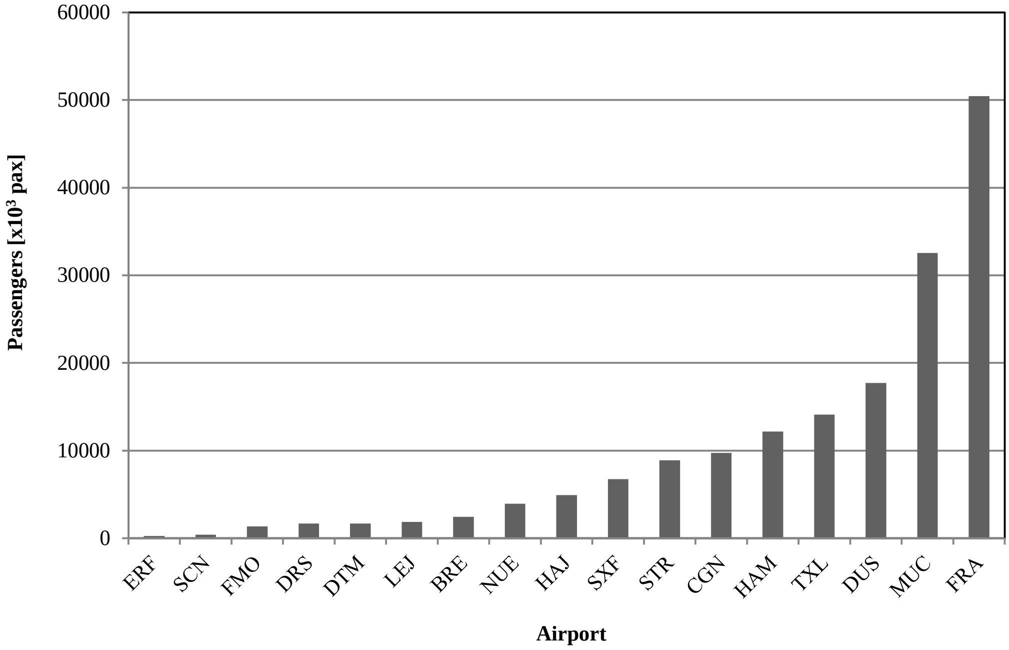

Figure 27 – Number of passengers served at the German international airports in 2009

In our study, we have focused on the 17 international airports, which are distributed across 14 metropolitan areas. In order to capture the behavior of regional passenger demand in multi-airport systems, the secondary airports serving those metropolitan areas were also considered in the study (passengers may be willing to use secondary airports in order to avoid the congested primary airports). The airports and metropolitan areas contemplated in the study are shown in Table 32.

Table 32 – Set of airports and metropolitan areas considered in the study

Metropolitan Area	Airport code	Airport name	International
Berlin	TXL	Berlin Tegel "Otto Lilienthal" airport	X
	SXF	Berlin-Schönefeld airport	X
Bremen	BRE	Bremen airport	X
Dresden	DRS	Dresden airport	X
Düsseldorf	DUS	Düsseldorf International airport	X
	CGN	Köln/Bonn airport	X
	DTM	Dortmund airport	X
	NRN	Weeze (Niederrhein) airport	
Erfurt	ERF	Erfurt-Weimar airport	X
Frankfurt	FRA	Frankfurt am Main airport	X
	HHN	Frankfurt-Hahn airport	
Hamburg	HAM	Hamburg-Fuhlsbüttel airport	X
	LBC	Lübeck Blankensee airport	
Hannover	HAJ	Hannover-Langenhagen airport	X
Leipzig	LEJ	Leipzig/Halle airport	X
München	MUC	München airport	X
Münster	FMO	Münster Osnabrück International airport	X
Nürnberg	NUE	Nürnberg airport	X
Saarbrücken	SCN	Saarbrücken airport	X
	ZQW	Zweibrücken airport	
Stuttgart	STR	Stuttgart airport	X
	FKB	Baden-Baden/Karlsruhe airport	

3. Optimization model

The study of the long-term evolution of the main airport network of Germany was based on an optimization model. We start this section by presenting the optimization model developed to address the problem. Then, we describe the heuristic method used to solve it. The type of results that can be expected from the application of the model is then illustrated for a small-size, hypothetical airport network.

3.1 Model formulation

The model used in the study is derived from the one presented in Chapter 2. Both models apply to a set of metropolitan areas (or centers), and determine the expansion actions to apply to the centers in order to maximize total system throughput, while coping with future demand and complying with a given budget. There are three fundamental differences between the two models. Firstly, the model proposed here applies to a set of metropolitan areas which can either be served by an airport/multi-airport system, or not – it is a location model in addition to being a capacity expansion model. Secondly, this model considers the possibility of building a new airport in metropolitan areas which are presently not served by an airport, regarding it will serve a given minimum traffic amount. Thirdly, this model considers explicitly the complementarity and competition between air travel and land travel modes. This makes possible to consider the response in travelers' behavior due to congestion problems at the airports, which can, for instance, switch to other modes with lower travel cost (in the model presented in Chapter 2, the modal split factor, ϕ, was used to determine the portion of trips made by air mode as a function of travel distance between centers).

The following notation was used:

<u>Sets</u>:

$\boldsymbol{N}$ - set of centers (metropolitan areas), served by airport or not

$\boldsymbol{N^*}_{jkr}$ - set of airports included in route r connecting centers j and k

$\boldsymbol{L}$ - set of flight legs

$\boldsymbol{L}_j$ - set of flight legs with start point at the airport in center j

$\boldsymbol{L}_{jkr}$ - set of flight legs included in route r connecting centers j and k

$\boldsymbol{R}_{jk}$ - set of routes connecting centers j and k

$\boldsymbol{R}_l$ - set of routes containing flight leg l

$\boldsymbol{M}_j$ - set of expansion actions applicable to center j

<u>Parameters:</u>

p_j - population of center j

d_{jk} - travel distance between centers j and k

s_j - initial airport capacity of center j (if center j is not served by airport, s_j=0)

w_{min} - minimum utilization rate required to build a new airport

g_{jm} - capacity increase in center j due to the application of expansion action m

e_{jm} - cost of applying expansion action m to center j

b - budget available for expansion actions

α, μ, β, γ - statistical calibration parameters.

<u>Decision variables:</u>

q_{jk} - O-D traffic flow between centers j and k (using any of the travel modes available)

w_j - traffic flow at the airport in center j

u_l - traffic flow in flight leg l

v_{jkr} - traffic flow in route r connecting centers j and k

c_{jk} - average travel cost between centers j and k

c_{jkr} - travel cost for route r connecting centers j and k

z_j - final capacity of center j

x_j - congestion tax to apply in center j

y_{jm} - binary variable equal to 1 if expansion action m is applied to center j, and equal to 0 otherwise.

The variables and parameters related with traffic flows on the legs are measured in number of passengers (per day), and the ones related with airport capacities and traffic flows in the centers are defined in enplanements (that is, passenger departures). Travel costs are defined in EUR/passenger.

Using the notation above, the mathematical formulation of the model is as follows:

$$\max \sum_{j \in \mathbf{N}} w_j \tag{1}$$

subject to:

$$q_{jk} = \alpha \left(p_j p_k \right)^{\mu} c_{jk}^{-\beta}, \ \forall j,k \in \boldsymbol{N} \tag{2}$$

$$v_{jkr} = \frac{e^{-\gamma c_{jkr}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkp}}} q_{jk}, \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk} \tag{3}$$

$$u_l = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{r \in \boldsymbol{R}_l} v_{jkr}, \ \forall l \in \boldsymbol{L} \tag{4}$$

$$w_j = \sum_{l \in \boldsymbol{L}_j} u_l \,, \quad \forall j \in \boldsymbol{N} \tag{5}$$

$$c_{jkr} = C_{jkr}^{land} + \left[\sum_{l \in \boldsymbol{L}_{jkr}} C_1(d_l, u_l) + \sum_{n \in \boldsymbol{N}^*_{jkr}} \left[C_2\left(\frac{w_n}{z_n}\right) + x_n \right] \right], \quad \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk} \tag{6}$$

$$c_{jk} = \frac{\sum_{r \in \boldsymbol{R}_{st}} c_{jkr} v_{jkr}}{q_{jk}}, \quad \forall j,k \in \boldsymbol{N} \tag{7}$$

$$z_j \geq w_j, \quad \forall j \in \boldsymbol{N} \tag{8}$$

$$\sum_{m \in \boldsymbol{M}_j} g_{jm} y_{jm} \leq \frac{w_j}{w_{\min}}, \quad \forall j \in \boldsymbol{N} \mid s_j = 0 \tag{9}$$

$$z_j = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm}\, y_{jm}, \quad \forall j \in \boldsymbol{N} \tag{10}$$

$$\sum_{m \in \boldsymbol{M}_j} y_{jm} \leq 1, \quad \forall j \in \boldsymbol{N} \tag{11}$$

$$\sum_{j \in \boldsymbol{N}} \sum_{m \in \boldsymbol{M}_j} e_{jm}\, y_{jm} \leq b \tag{12}$$

$$y_{jm} \in \{0,1\}, \quad \forall j \in \boldsymbol{N}, \ \forall m \in \boldsymbol{M}_j. \tag{13}$$

The objective function (1) of the model expresses the maximization of total system throughput, as measured by the total number of enplanements made within the airport network (the number of enplanements at centers not served by airport is zero).

Constraints (2) are the O-D demand functions relating the traffic flows between each pair of centers (using any of the travel modes available) with their population and with the average (generalized) travel cost between the centers.

Constraints (3) assign the O-D traffic flows to routes as a function of the average travel cost through a logit model. The set of routes connecting each pair of centers define how trips are made. Trips may include up to three parcels: *i*) one parcel – if a trip is only made by air mode (the origin airport is located in the origin center and the destination airport is located in the destination center), or if a trip is only made by one of the land transport modes (it is not considered the possibility of using two land modes in trips made entirely by land); *ii*) two parcels – if the origin airport is located in the origin center and the destination airport is not located in the destination center, of if the origin airport is not located in the origin center and the destination airport is located in the destination center (one of the land modes is used in the initial and final parcels of the trip, respectively); *iii*) trips with three parcels, in which the origin airport is not located in the origin center and the destination airport is not located in the destination center, are only allowed when both origin and destination centers are not served by airport.

Take for instance the network constituted by four centers represented in Figure 28. Centers *j*, *m* and *n* are served by airports, whereas Center *k* is not. The airports located in Centers *j* and *m* are hub airports, and the airport in Center *n* is a non-hub airport, serving only as trip origins or destinations. Flight legs exist between all airports. All centers are connected directly by land mode 1, and a direct connection by land mode 2 exists between Centers *m* and *k*, *k* and *j*, and *j* and *n*. The possible routes connecting centers *j* and *k* are: 1) travel by land mode 1 directly; 2) travel by land mode 2 directly; 3) travel by air from *j* to *m*, and by land mode 1 from *m* to *k*; 4) travel by air from *j* to *m*, and by land mode 2 from *m* to *k*; 5) travel by air from *j* to *n*, and by land mode 1 from *n* to *k*; and 6) travel by air from *j* to *n* through *m*, and by land mode 1 from *n* to *k*.

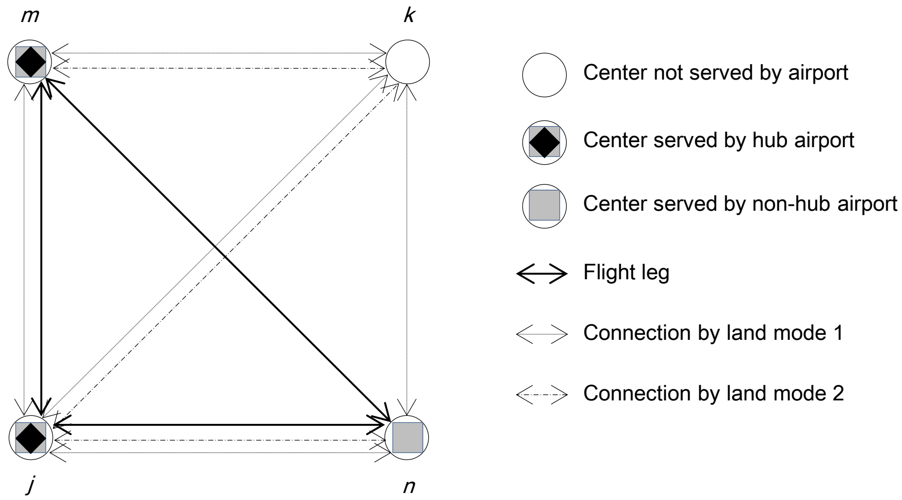

Figure 28 – Hypothetical network with four centers connected through three travel modes

Constraints (4) calculate the traffic flow in each flight leg by summing the traffic flows in the routes containing those legs.

Constraints (5) compute the enplanements at the centers (airports) by summing the traffic flows in the legs with start point in those centers.

Constraints (6) compute the travel cost for each route. This cost is calculated by summing the cost for the parcel of the trip made by land mode (if exists), and the cost for the flight leg(s) and the cost for the airports included in that route (if a parcel of the trip is made by air). The cost for the parcel of the trip made by land mode (first term) is a parameter and do not depend on traffic flow. The cost for the flight legs (second term) is assumed to increase with travel distance, and, because of economies of scale, to decrease with traffic flow. The cost for the airports (third term) is assumed to be fixed below a given utilization rate and then to increase because congestion makes airport operations more expensive and time-consuming. If a center is not served by an airport, the airport cost is set to a number large enough to disregard the routes using it as origin, connection or destination airport. The airport cost may also include a congestion tax levied by the aviation authority in order to regulate the utilization of airport capacity in case of excess demand.

Constraints (7) calculate the average (generalized) travel cost for each pair of centers by summing the cost for the routes connecting the centers weighted by the respective traffic flow and then dividing by the total traffic flow.

Constraints (8) establish that the airport capacity of the centers must be able to accommodate the traffic flow.

Constraints (9) state that a new airport is only built in a center without airport regarding it will operate at a minimum utilization rate.

Constraints (10) state that the capacities of the centers are given by the sum of their initial capacities and the capacity increase due to the expansion action applied.

Constraints (11) ensure that at most one expansion action will be applied for each center.

Constraints (12) guarantee that the total expenditure will comply with the budget available for expansion actions.

Finally, constraints (12) define the capacity expansion variables as binary (all other decision variables are non-negative real numbers).

3.2 Solution method

The complex optimization model presented previously is extremely difficult (if not impossible) to solve to exact optimality. Thus, a heuristic solution method was developed to solve the model. This solution method is based on the one proposed in Chapter 3. It comprises two iterative procedures: (1) determination of capacity expansion actions to apply to the airport network (candidate solutions); (2) determination of equilibrium flows and travel costs. The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the centers consistent with the budget available, and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The second (lower-level) procedure determines the equilibrium traffic flows and costs for each candidate solution. It also determines the congestion taxes to apply in order to cancel out excess demand situations that might occur in some airport(s). The two procedures are executed iteratively until total system throughput ceases to increase. The solution method is outlined in Figure 29.

The determination of candidate solutions can be performed using various types of algorithms. The local search Add+Interchange algorithm (AIA) was selected as it provided good solutions at reasonable computational effort for the model presented in Chapter 2. The AIA starts with the initial airport network and, in successive iterations, selects the one-level airport upgrade change that allows the best improvement of the objective function, until no further improvement is possible (within the budget available). For the centers currently not served by airport, the first possible expansion action consists of building a new airport with capacity layout 1. Then, starting with the solution found, it selects the combination of feasible one-level capacity swaps that allow the best improvement of the objective function (a possible capacity swap is to expand an airport one capacity level, and eliminate an airport with capacity layout 1 in a center currently not served by airport). Solutions which do not comply with the minimum flow requirement at centers currently not served by airports (expressions 9) are rejected.

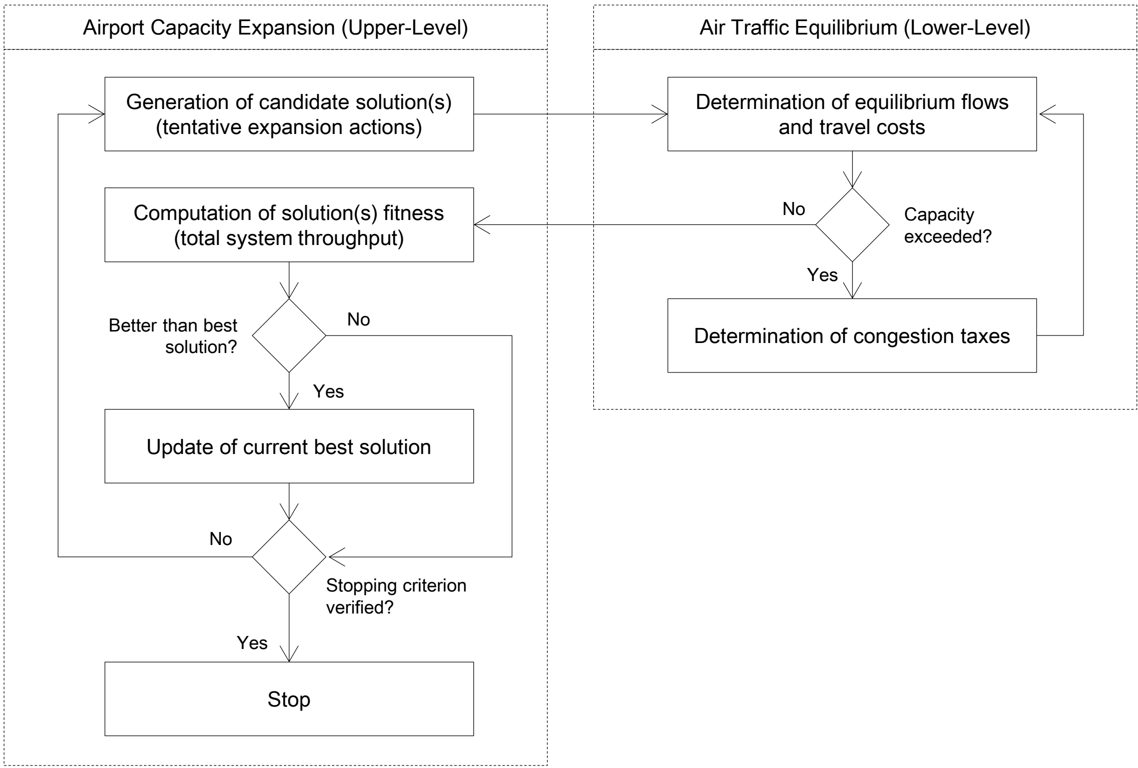

Figure 29 – Outline of the algorithm

The traffic equilibrium procedure starts by defining the set of routes connecting each pair of centers, $\boldsymbol{R}_{jk}$, and the set of flight legs, $\boldsymbol{L}$, for the current candidate solution (as well as the correspondent sets $\boldsymbol{N^*}_{jkr}$, $\boldsymbol{L}_j$, $\boldsymbol{L}_{jkr}$, and $\boldsymbol{R}_l$). Then, the traffic flows at set to zero and it is calculated the travel cost for each itinerary r connecting O-D pair j-k (for all j and k in $\boldsymbol{N}$ and for all r in $\boldsymbol{R}_{jk}$), c_{jkr}, through expression (6). With the average travel cost for each O-D pair j-k, c_{jk}, the traffic between j and k, q_{jk}, is calculated through expression (2). The traffic between j and k is then assigned to each route r in $\boldsymbol{R}_{jk}$ through expression (3). After assigning traffic to routes, the leg and airport flows are calculated using expressions (4) and (5), respectively. Until convergence (that is, until the flows on the legs are the same in consecutive iterations except for a small tolerance), the travel costs are updated according to the flows on the legs and the utilization rate of airports, and the traffic flows are updated as a function of the current travel costs. The equilibrium flows (and costs) are obtained using the successive averages method (Robbins and Monro 1951, Powell and Sheffi 1982, Ortúzar and Willumsen 2011, p. 370). After computing the equilibrium flows, if the capacities of some airports are exceeded (i.e., if expression 8 is violated for some airports), congestion taxes are successively applied to the airport with the smallest positive excess demand, until a solution where airports are not affected by excess demand is found.

For a detailed explanation of the solution method the reader is referred to Chapter 3.

3.3 Application example

The type of results that can be obtained through the application of the optimization model presented in Section 3.1 will be illustrated for Instance #1 of a set of random instances generated for a region with six population centers (the same instance used in Chapter 2). The application consists in analyzing the implications for the airport network of a 25 percent increase of the size of all population centers and in determining the expansion actions to implement in response to the population increase as a function of the budget available.

Below we provide detailed information on the data used to run the model and on the results obtained through its application.

3.3.1 Data

The population centers are randomly distributed over a square-shaped region with 4,000 × 4,000 km^2 (Table 33). The sizes of the population centers were randomly determined to follow Zipf's rank-size rule considering the maximum population of 20 million for the largest center.

Table 33 – Population and coordinates of the centers

Center	Coordinates (km)		Population (10^6 inhabitants)
	X	Y	
1	369	3026	17.162
2	3722	1535	7.180
3	2685	1534	4.474
4	3539	2078	3.295
5	952	1051	2.658
6	3014	3637	1.948

Airports can have six possible layouts (besides capacity layout 0, which stands for a center without airport). The possible layouts and corresponding airport capacities are listed in Table 34.

Table 34 – Possible airport layouts and corresponding increase in capacity (x10^3 pax/day)

Layout	Runway configuration	Capacity (10^3 pax/day)
1	Single runway	40
2	Two close parallel runways	60
3	Two medium spaced parallel runways	70
4	Two independent parallel runways	80
5	Three runways (two close runways plus one)	100
6	Four runways (two pairs of close parallel runways)	120

The demand function, the route choice (logit) model, the cost functions (C^{land}, C_1 and C_2), and the minimum flow constraints are as follows:

$$q_{jk} = 1.8 p_j p_k c_{jk}^{-0.5}, \ \forall j,k \in \boldsymbol{N} \tag{14}$$

$$v_{jkr} = \frac{e^{-0.03 c_{jkr}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-0.03 c_{jkp}}} q_{jk}, \ \forall j,k \in \boldsymbol{N}, r \in \boldsymbol{R}_{jk} \tag{15}$$

$$C_{jk}^{land} = 0.07 l_{jk}, \ \forall j,k \in \boldsymbol{N} \tag{16}$$

Where $C^{land}{}_{jk}$ is the travel cost by land mode between centers j and k, and l_{jk} is the (Euclidean) distance between centers j and k. Only one land transport mode is available (with a travel cost of 0.07 EUR/km), and a direct connection exists between all centers.

$$C_1(d_l, u_l) = \begin{cases} \left(1 - \frac{0.5}{20} \times u_l\right) \times 0.06 \times d_l \Leftarrow u_l < 20 \\ 0.03 \times d_l \Leftarrow u_l \geq 20 \end{cases}, \ \forall l \in \boldsymbol{L} \tag{17}$$

$$C_2\left({w_n}/{z_n}\right) = \begin{cases} 20 \Leftarrow {w_n}/{z_n} \leq 0.8 \\ 100 \times {w_n}/{z_n} - 60 \Leftarrow {w_n}/{z_n} > 0.8 \end{cases}, \ \forall n \in \boldsymbol{N} \tag{18}$$

$$\left(\sum_{m \in \boldsymbol{M}_j} g_{jm} y_{jm} - s_j\right) \leq \frac{w_j}{0.25}, \ \forall j \in \boldsymbol{N} \tag{19}$$

The units for the variables included in these expressions are: q_{jk}, v_{jkr}, u_l, w_n, and z_n, 10^3 pax/day; p_j, million inhabitants; C^{land}, C_1, and C_2, EUR/pax; and d_{jk} and d_l, km.

The existing airport network is described in Figure 30 and Table 35. Centers 1 to 4 (the four largest centers) are served by single runway airports (Layout 1), and Centers 5 and 6 are not served by airports. The airports of the two largest centers (Centers 1 and 2) are hub airports, and the other airports are non-hub airports, serving only as trip origins or destinations. The hub airport in Center 1 is congested since the utilization rate is 100% (however, its capacity is enough to serve all demand as the congestion tax is set to zero). The remaining airports operate at about half of their capacity, and therefore do not present congestion problems. The total system throughput is 99.4×10^3 pax/day. The route flows are shown in Table 36, the traffic for the flight routes in Table 37, the traffic for the flight legs in Table 38, and the traffic for the land legs in Table 39. The air mode is the most used as centers are located at a considerable distance. Only between Centers 2 and 4 (at a distance of 573km), the land mode is the most used (2.5×10^3 pax/day, against 1.5×10^3 pax/day using air mode). Overall, 60.0% of trips are made entirely by air mode, 5.4% are made only by land mode, and 34.6% are made with a combination of air and land transport modes. The latter correspond mostly to trips to and from Centers 5 and 6 (which are not served by airport). The traffic by air mode (accounting for the trips made entirely by air and by a combination of air and land modes), is predominantly non-stop (85.6%), whereas 14.4% of trips include an intermediate connection at a hub airport (9.1% at hub airport 1, and 5.3% at hub airport 2).

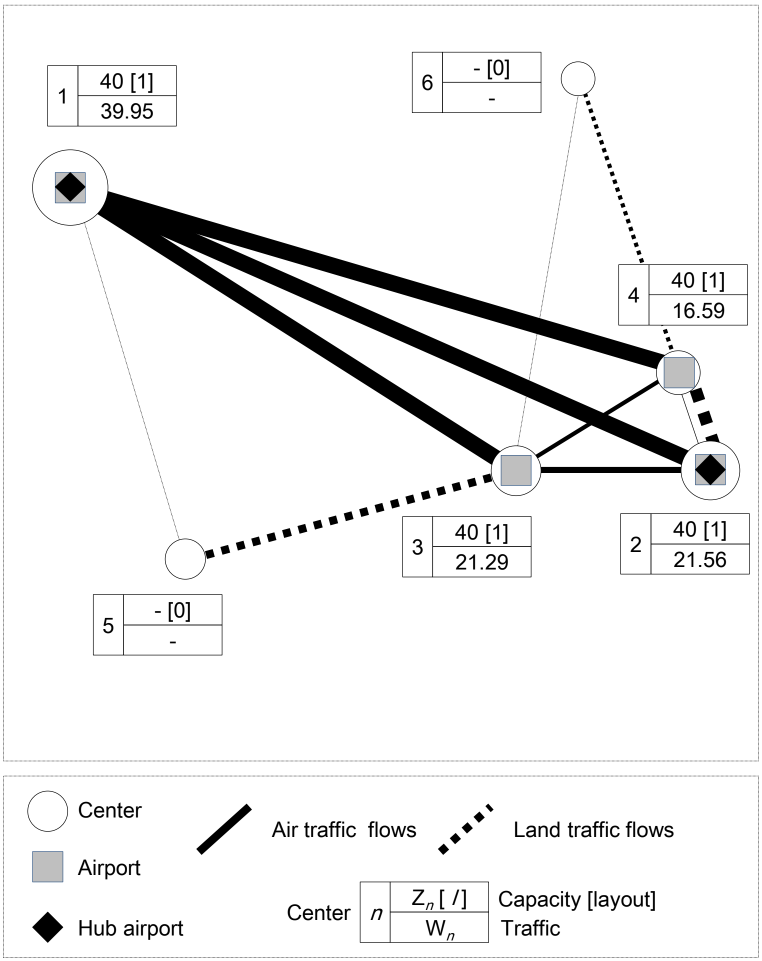

Figure 30 – Existing airport network

Table 35 – Airport information for the existing airport network

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax (EUR/pax)
1	40	40.0	100	39.9	0.0
2	40	21.6	54	20.0	0.0
3	40	21.3	53	20.0	0.0
4	40	16.6	41	20.0	0.0
5	-	-	-	-	-
6	-	-	-	-	-

Table 36– Route flows in the existing airport network

Center		Assigned routes (traffic, 10^3 pax/day)		
Origin	Destination			
1	2	**1-1-1-2-2 (8.8)**	1-1-1-4-2 (3.0)	-
1	3	**1-1-1-3-3 (7.2)**	**1-1-2-3-3 (0.9)**	-
1	4	1-1-1-2-4 (0.9)	**1-1-1-4-4 (3.5)**	**1-1-2-4-4 (1.0)**
1	5	1-1-1-3-5 (3.4)	-	-
1	6	1-1-1-4-6 (2.5)	-	-
2	1	**2-2-1-1-1 (8.8)**	2-4-1-1-1 (3.0)	-
2	3	**2-2-2-3-3 (3.2)**	2-4-3-3-3 (0.9)	-
2	4	<u>2-2-2-2-4 (2.5)</u>	**2-2-2-4-4 (1.5)**	-
2	5	2-2-1-3-5 (1.2)	-	-
2	6	2-2-1-4-6 (0.9)	-	-
3	1	**3-3-1-1-1 (7.2)**	**3-3-2-1-1 (0.9)**	-
3	2	**3-3-2-2-2 (3.2)**	3-3-3-4-2 (0.9)	-
3	4	3-3-2-2-4 (0.3)	**3-3-2-4-4 (0.4)**	**3-3-3-4-4 (1.1)**
3	5	3-3-1-1-5 (0.9)	-	-
3	6	3-3-1-4-6 (0.6)	-	-
4	1	4-2-1-1-1 (0.9)	**4-4-1-1-1 (3.5)**	**4-4-2-1-1 (1.0)**
4	2	<u>4-2-2-2-2 (2.5)</u>	**4-4-2-2-2 (1.5)**	-
4	3	4-2-2-3-3 (0.3)	**4-4-2-3-3 (0.4)**	**4-4-3-3-3 (1.1)**
4	5	4-4-1-3-5 (0.6)	-	-
4	6	4-4-1-3-6 (0.4)	-	-
5	1	5-3-1-1-1 (3.4)	-	-
5	2	5-3-1-2-2 (1.2)	-	-
5	3	5-1-1-3-3 (0.9)	-	-
5	4	5-3-1-4-4 (0.6)	-	-
5	6	5-3-1-4-6 (0.3)	-	-
6	1	6-4-1-1-1 (2.5)	-	-
6	2	6-4-1-2-2 (0.9)	-	-
6	3	6-4-1-3-3 (0.6)	-	-
6	4	6-3-1-4-4 (0.4)	-	-
6	5	6-4-1-3-5 (0.3)	-	-

Notes:

(i) Figures in **bold** denote trips made entirely by air mode, and figures <u>underlined</u> denote trips made entirely by land mode;

(ii) routes are defined by 5 indexes: origin center (*j*) - origin airport (*m*) - connecting airport (*n*) - destination airport (*o*) - destination center (*k*). The sequences *j-j-n-o-k* and *j-j-j-o-k* denote trips between airports *j* and *o* by air mode (through hub *n* and direct, respectively) and using land mode from *o* to *k*. The sequence *j-j-j-j-k* denotes trips made only by land mode between *j* and *k*.

Table 37 – Traffic on the flight routes in the existing airport network

Airport		Traffic (10^3 pax/day)		
Origin	Destination	Non-stop	Through Airport 1	Through Airport 2
1	2	9.76	-	-
1	3	11.41	-	0.90
1	4	8.94	-	1.03
2	3	3.51	1.25	-
2	4	1.52	0.88	-
3	4	2.01	1.82	0.38

Table 38 – Traffic on the flight legs in the existing airport network

	Traffic (10^3 pax/day)					
Origin airport	Destination airport					
	1	2	3	4	5	6
1	0.0	13.8	14.5	11.6	0.0	0.0
2	13.8	0.0	4.8	2.9	0.0	0.0
3	14.5	4.8	0.0	2.0	0.0	0.0
4	11.6	2.9	2.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0

Table 39– Traffic on the land legs in the existing airport network

	Traffic (10^3 pax/day)					
Origin airport	Destination airport					
	1	2	3	4	5	6
1	0.0	0.0	0.0	0.0	0.9	0.0
2	0.0	0.0	0.0	10.1	0.0	0.0
3	0.0	0.0	0.0	0.0	5.4	0.4
4	0.0	10.1	0.0	0.0	0.0	4.2
5	0.9	0.0	5.4	0.0	0.0	0.0
6	0.0	0.0	0.4	4.2	0.0	0.0

The expenditure involved in the expansion of airports is presented in Table 40.

Table 40 – Airport expansion costs (EUR 10^8)

Cost (10^8 \$)						
Initial airport layout	Final airport layout					
	1	2	3	4	5	6
No airport	8	10	12	14	16	18
1	-	6	8	9	12	14
2	-	-	5	6	9	11
3	-	-	-	4	7	9
4	-	-	-	-	6	8
5	-	-	-	-	-	5

3.3.2 Results

As stated before, the application consists in determining the expansion actions to implement in response to a 25% increase of the size of all population centers as a function of the budget available for the improvement of the existing airport network.

According with the outcomes of the optimization model, if nothing is done (budget b=0), the hub airport located in Center 1 would become seriously congested, and it would be necessary to apply a congestion tax of 249.3 EUR/pax to regulate the utilization of the airport (avoiding excess demand situations). The airports located in Centers 2, 3 and 4 would continue to operate at low utilization rates, and therefore would not present congestion problems – see Figure 31 and Table 41. The total system throughput would rise to 108.7×10^3 pax/day (+9.3%). Capacity shortage at the airport in Center 1 would prevent a larger increase in system throughput, and some traffic would be diverted to the land transport mode. Overall, the proportion of trips made by air mode would decrease by 2.5%, and the total traffic by land mode would increase by

23.2% (mainly due to the increase of the number of trips by land mode with origin and destination in Center 1).

If no budget constraints were considered for expanding the airport network, the layout of the airports in Centers 1 and 2 would be improved to "two independent parallel runways" (Layout 4) and "two medium spaced parallel runways" (Layout 3), respectively, and single runway airports would be built in Centers 5 and 6 (Figure 32 and Table 43). The capacity of the airports in Centers 3 and 4 would remain unchanged. The total expenditure involved in these transformations to the airport network is 33×10^8 EUR. All airports would operate at a utilization rate below 80%, and therefore would not present considerable congestion problems. The elimination of congestion problems at the airports (thus, reducing the travel cost by air mode) would divert a considerable amount of traffic from the land mode – the total traffic by land mode would be 32.9×10^3 pax/day, which corresponds to a decrease of 36.3% relatively to the "do nothing" solution. The total system throughput would grow to 184×10^3 pax/day, which corresponds to an increase of 84.6% relatively to the initial airport network, and 68.9% relatively to the "do nothing" solution (b=0).

If only 16.5×10^8 EUR could be made available for airport expansion actions (half of the budget needed to expand freely the airport network), only the airport in Center 1 would be improved, from Layout 1 to Layout 3 ("two medium-spaced parallel runways"), and a new airport with one runway would be built in Center 5 (Figure 33 and Table 45). Total system throughput would reach 169.6×10^3 pax/day (increase of 70.6% relatively to the initial airport network, and 56.0% relatively to the "do nothing" solution). This means that approximately 81% of the possible gains in total throughput could be made with only a little more than 50% of the budget needed to completely eliminate congestion problems in the airport network (however, the airports in Centers 1 and 2 would present some congestion problems). The total traffic by land mode would be 52.4×10^3 pax/day, which corresponds to an increase of 1.3% relatively to the "do nothing" solution.

4. Model estimation

The optimization model embodies a model that simulates the traffic flows and travel costs in the airport network considering the (expanded) capacities of the airports. The simulation model encompasses statistical calibration parameters. This section presents the approach we have adopted to calibrate these parameters (subsection 4.1), as well as the data used (subsection 4.2). Then, the calibration parameters considered for the application to the airport network of Germany are explained (subsection 4.3), and the results obtained through the calibration are presented (subsection 4.4).

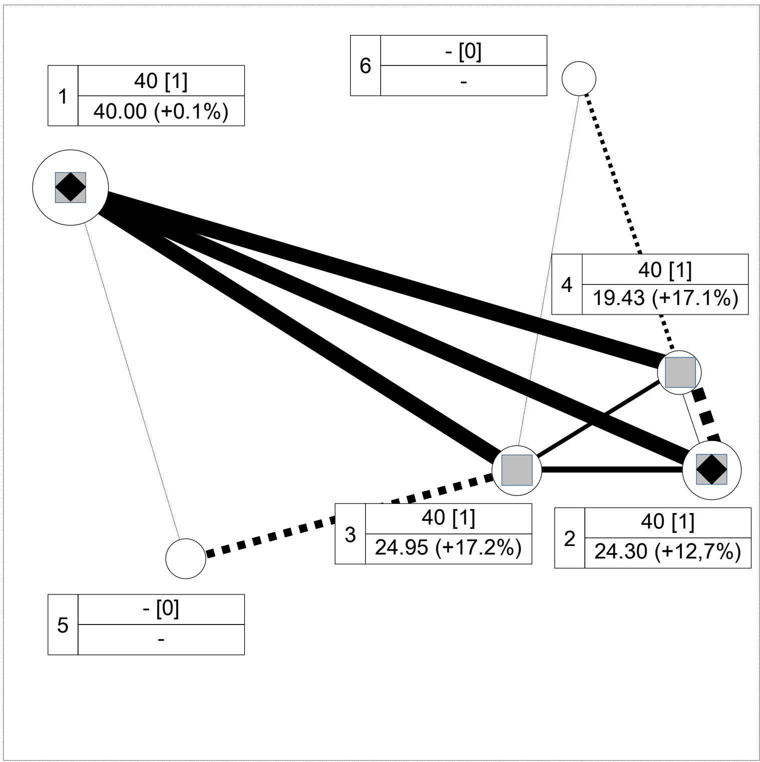

Figure 31 – Optimum airport network for *b* = 0

Table 41 – Airport information for the optimum airport network with *b* = 0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	40	40.0	100	40.0	249.3
2	40	24.3	61	20.0	0.0
3	40	25.0	62	20.0	0.0
4	40	19.4	49	20.0	0.0
5	-	-	-	-	-
6	-	-	-	-	-

Table 42 – Traffic on the flight legs for the optimum airport network with *b* = 0

Origin	Destination airport					
airport	1	2	3	4	5	6
1	0.0	13.2	14.6	12.2	0.0	0.0
2	13.2	0.0	7.2	4.0	0.0	0.0
3	14.6	7.2	0.0	3.2	0.0	0.0
4	12.2	4.0	3.2	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0

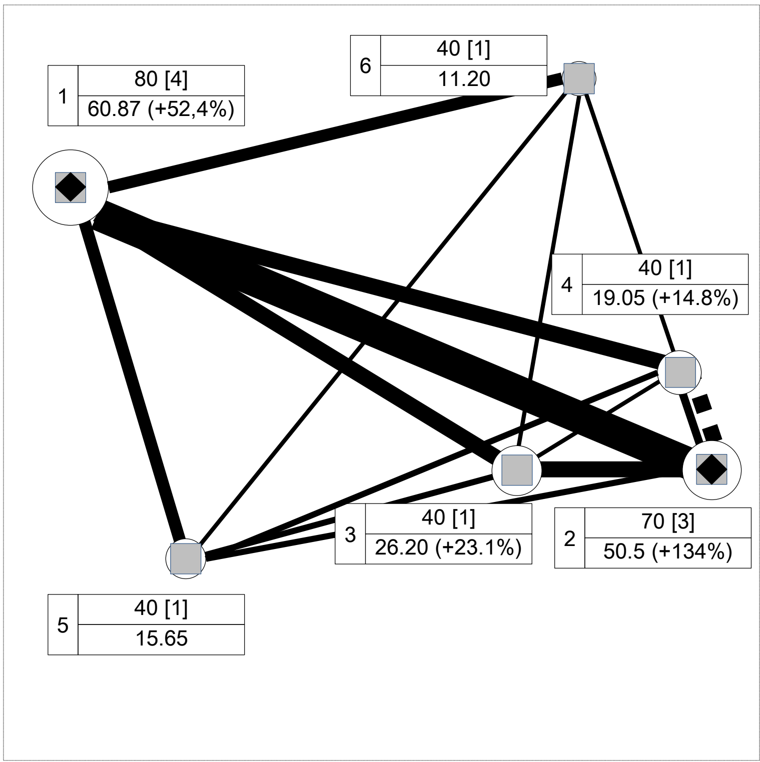

Figure 32 – Optimum airport network for *b* = EUR 33x10^8

Table 43 – Airport information for the optimum airport network with *b* = EUR 33x10^8

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	80	60.9	76	20.0	0.0
2	70	50.5	72	20.0	0.0
3	40	26.2	66	20.0	0.0
4	40	19.1	48	20.0	0.0
5	40	15.7	39	20.0	0.0
6	40	11.2	29	20.0	0.0

Table 44 – Traffic on the flight legs for the optimum airport network with *b* = EUR 33x10^8

Origin	Destination airport					
airport	1	2	3	4	5	6
1	0.0	28.7	10.6	7.1	9.2	5.3
2	28.7	0.0	9.8	6.3	3.0	2.8
3	10.6	9.8	0.0	3.0	1.7	1.1
4	7.1	6.3	3.0	0.0	1.2	1.5
5	9.2	3.0	1.7	1.2	0.0	0.5
6	5.3	2.8	1.1	1.5	0.5	0.0

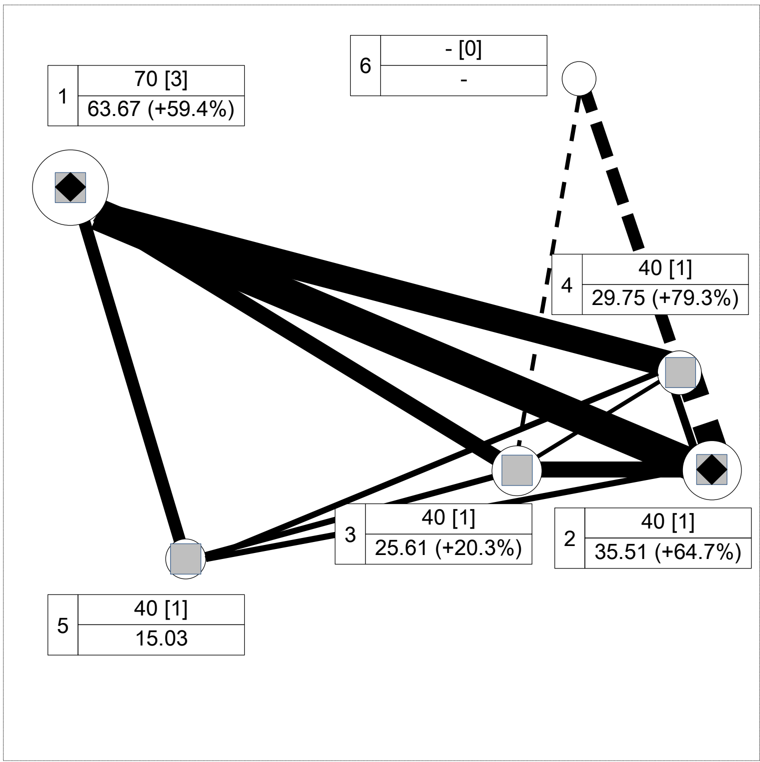

Figure 33 – Optimum airport network for *b* = EUR 16.5x10^8

Table 45 – Airport information for the optimum airport network with *b* = EUR 16.5x10^8

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	70	63.7	91	31.0	0.0
2	40	35.5	89	28.8	0.0
3	40	25.6	64	20.0	0.0
4	40	29.8	74	20.0	0.0
5	40	15.0	39	20.0	0.0
6	-	-	-	-	-

Table 46 – Traffic on the flight legs for the optimum airport network with *b* = EUR 16.5x10^8

Origin	Destination airport					
airport	1	2	3	4	5	6
1	0.0	20.9	12.7	20.7	9.3	0.0
2	20.9	0.0	7.8	4.3	2.6	0.0
3	12.7	7.8	0.0	3.4	1.8	0.0
4	20.7	4.3	3.4	0.0	1.4	0.0
5	9.3	2.6	1.8	1.4	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0

4.1 Calibration approach

The approach used to calibrate the simulation model consisted in finding values for the statistical parameters such that the modeled traffic flows in the flight legs (u_l) matched the traffic flows observed (u_l^{obs}) within the airport network. Specifically, we looked for the values of parameters that solve the following optimization model:

$$\min \sum_{l \in \boldsymbol{L}} \left(\frac{u_l - u_l^{obs}}{u_l^{obs}} \right)^2 - G\left(\sum_{j \in \boldsymbol{N}} w_j - \sum_{j \in \boldsymbol{N}} w_j^{obs} \right) \tag{20}$$

subject to:

Constraints (2) – (8)

$$z_j = s_j, \ \forall j \in \boldsymbol{N} \tag{21}$$

The objective function (20) of this model expresses the minimization of the sum of the relative quadratic deviations between modeled and observed traffic flows on the flight legs, plus a penalty dependent on the difference between the total modeled flows and the total observed flows (G denotes a number large enough to penalize parameter values which lead to modeled flows different from the observed ones), and constraints (2) to (8) and (21) simulate the traffic flows and travel costs in the network for given airport capacities.

For solving this optimization model, we used the Nelder-Mead algorithm, considered to be one of the most sophisticated global optimization algorithms (Nelder and Mead 1965, Powell 1973, Conn et. al 2009). This algorithm works with a population of solutions, each one corresponding to a given combination of values for the parameters. Let the population of solutions be represented by $POP = \{\lambda_1, \ldots, \lambda_j, \ldots, \lambda_{dim}\}$, where λ_j represents solution *j*, and *dim* represents the size of the population. The initial population of solutions is randomly generated within a given range for each parameter – for all solutions *j* and parameters *k*, $\lambda^{k\_min} < \lambda^k_j < \lambda^{k\_max}$, where λ^{k_min} and λ^{k_max} represent, respectively, the minimum and maximum values for parameter *k* in the initial population. For each solution generated, the network is simulated according to equations (2) to (8), and the value (*fitness*) of the solution is computed through the objective-function (20). Then, in consecutive iterations, the population evolves toward better solutions through the application of four procedures: reflection, expansion, contraction, and shrinkage. The process is repeated for a given maximum number of iterations with no improvement in the best solution. If the best solution improved throughout the iterative process, the initial range for the parameters (as defined by λ^{k_min} and λ^{k_max}) is centered in the best values and the iterative process is repeated; otherwise, the algorithm stops (the pseudo-code of the Nelder-Mead algorithm is shown in Figure 25 in Chapter 4).

4.2 Data

The simulation model was calibrated using four types of data: (1) traffic data for the trips made within the airport network; (2) socio-economic data for the metropolitan areas; (3) capacity data for the airports; and (4) travel cost data by land mode between the metropolitan areas. All data were obtained for 2008, which was the most recent data available at the time the study was initiated.

4.2.1 Air traffic data

The traffic flows in the flight legs (u^{obs}) were provided by the European Center for Aviation Development (ECAD GmbH) based on OAG original data. These values (in number of passengers per year) were aggregated to compute the traffic flows between the metropolitan areas, and were converted in daily traffic flows assuming an equal distribution of traffic across the year.

The traffic flows in the flight legs include traffic with origin or destination in airports not included in the network under considerations (mostly, traffic from and to international airports). This traffic is considered through the inclusion of 11 international centers in $\boldsymbol{N}$ (in addition to the 14 German centers depicted in Table 32): Amsterdam (representing the aggregate traffic from the Netherlands and Belgium), Stockholm (Sweden, Norway, Finland and Denmark), Paris (France), London (United Kingdom and Republic of Ireland), Rome (Italy), Madrid (Spain and Portugal), Zurich (Switzerland), Warsaw (Poland), Vienna (Austria, Czech Republic, Hungary and Slovakia), and Istanbul (Turkey). The connecting traffic at German airports with origin and destination at airports not included in the network (which are not considered in the simulation model, but must be taken into account in the design of the airport network) were also obtained from OAG data.

4.2.2 Socio-economic data

The population of the metropolitan areas of Germany was obtained from DESTATIS (2011). The population is provided at the level of the independent cities. The aggregated values for the metropolitan areas were obtained by summing the individual values for the independent cities within 50 km of the airports serving the metropolitan areas. The population of the international centers (equal to the aggregate population of the representative countries) was obtained from OECD (2012). The values obtained for the population of the metropolitan areas are given in Table 47.

Table 47 – Population of the metropolitan areas

Metropolitan Area	Population (10^6 inhabitants)
Berlin	3.9
Bremen	1.5
Dresden	1.8
Düsseldorf	12.0
Erfurt	1.2
Frankfurt	5.4
Hamburg	4.2
Hannover	2.1
Leipzig	1.2
München	2.8
Münster	1.4
Nürnberg	2.1
Saarbrücken	1.3
Stuttgart	5.3
Amesterdam	27.2
Stockholm	24.8
Paris	64.4
London	65.8
Rome	59.8
Madrid	56.2
Zurich	7.7
Warsaw	38.1
Wien	34.2
Istambul	70.9

4.2.3 Capacity data

The annual airport capacity was obtained from ECAD (2010). The annual airport capacity was converted in daily capacity by assuming that it remains unchanged throughout the year. The airport capacity of the metropolitan areas was determined by summing the individual capacities of the airports located there. The international nodes were assumed to be capacity unconstrained. Table 48 presents the airport capacities in enplanements per year and per day, and the airport capacity of the metropolitan areas in enplanements per day.

4.2.4 Travel cost data

The train and car modes were considered to be an option for travelling between the metropolitan areas. The generalized travel costs by car were obtained by summing operation costs (reflecting e.g. cost of fuel and maintenance) and time costs. A unit operation cost of €0.30/km and a unit time cost of €15/hour were considered. The travel times (for calculating time costs) and travel distances (for calculating operation costs) were obtained from web-based map applications, considering that travelers select the least time route. The travel costs by train were obtained by summing ticket fares and time costs (reflecting travel time and schedule delay, which depends on the frequency of service). A unit time cost of €15/hour was also considered. The ticket fares, travel times and service frequencies for the train itineraries were obtained from the Deutsche Bahn website for the 14th of January of 2011 – an average travel cost was calculated by weighting the travel cost for all itineraries with the frequency offered throughout the day (it is assumed that travelers are distributed across available itineraries as a function of service frequency).

Table 48 – Capacity of the airports and metropolitan areas

Metropolitan Area	Airport	Average capacity (10^6 enplanements/year)	Average capacity (10^3 enplanements/day)	
			Airports	Metro. Areas
Berlin	TXL + SXF + THF	11.0	30.1	30.1
Bremen	BRE		8.2 (*)	8.2
Dresden	DRS		8.2 (*)	8.2
Düsseldorf	DUS	11.0	30.1	62.9
	CGN	6.0	16.4	
	DTM		8.2 (*)	
	NRN		8.2 (*)	
Erfurt	ERF		8.2 (*)	8.2
Frankfurt	FRA	28.0	76.7	84.9
	HHN	3.0	8.2	
Hamburg	HAM	7.8	21.2	29.4
	LBC		8.2 (*)	
Hannover	HAJ	4.0	11.0	11.0
Leipzig	LEJ		16.4 (**)	16.4
München	MUC	22.5	61.6	61.6
Münster	FMO		8.2 (*)	8.2
Nürnberg	NUE	3.0	8.2	8.2
Saarbrücken	SCN		8.2 (*)	16.4
	ZQW		8.2 (*)	
Stuttgart	STR	6.5	17.8	26.0
	FKB		8.2 (*)	

Notes: (*) airports with one runway for which capacity is not known, a capacity of 8.2×10^3 pax/day is considered (equal to the capacity of HHN and NUE, which have also one runway); (**) the capacity of LEJ airport (two independent parallel runways) is assumed to be twice the capacity of single runway airports (16.4×10^3 pax/day).

The definition of the admissible routes was made considering that a trip can include at most two travel modes (that is, at most one inter-modal transfer point), being possible to (1) travel only by air, car, or train from the origin center to the destination center; (2) travel by car to the origin airport and then by air to the destination center; (3) travel by train to the origin airport and then by air to the destination center, or by air from the origin center to the destination airport and then by train to the destination center; and (4) the total length of a trip cannot exceed 150% of the length of the direct link connecting the origin and destination centers (this assumption was made in order to reduce the number of routes with small probability to occur in practice, thus capturing in essence the observed traffic pattern while reducing computational effort to solve the model).

4.3 Model parameters

The demand function (constraints 2) is defined as follows:

$$q_{jk} = \begin{cases} \alpha\left(p_j p_k\right)^{\mu} c_{jk}^{\;-\beta 1} \Leftarrow j \notin \boldsymbol{N}' \wedge k \notin \boldsymbol{N}' \\ \alpha\left(p_j p_k\right)^{\mu} c_{jk}^{\;-\beta 2} \Leftarrow \left(j \in \boldsymbol{N}' \wedge k \notin \boldsymbol{N}'\right) \vee \left(j \notin \boldsymbol{N}' \wedge k \in \boldsymbol{N}'\right), \quad \forall j,k \in \boldsymbol{N} \\ 0 \Leftarrow j \in \boldsymbol{N}' \wedge k \in \boldsymbol{N}' \end{cases} \tag{21}$$

where ***N'*** denotes the set of international centers within ***N***, and α, μ, β_1 and β_2 are positive real numbers. Traffic between centers is defined by a gravity-type demand function, which depends upon parameters α, μ, and β_1 or β_2, for the cases when both origin and destination centers are located in Germany, or when the origin/destination center is in Germany and the destination/origin center is foreign, respectively. The difference between parameters β_1 and β_2 reflects the different response of travelers to travel cost for domestic and international trips.

The cost for the flight legs (in constraints 6) is assumed to increase with the power of travel distance, and to decrease with the power of traffic flow:

$$C_1(d_l, u_l) = \begin{cases} \sigma_1 \cdot d_l^{\upsilon} \cdot u_l^{\varpi} \Leftarrow l \notin \boldsymbol{L'} \\ \sigma_2 \cdot d_l^{\upsilon} \cdot u_l^{\varpi} \Leftarrow l \in \boldsymbol{L'} \end{cases}, \quad \forall l \in \boldsymbol{L} \qquad (22)$$

where ***L'*** denotes the set of flight legs with origin/destination in German centers and destination/origin in international centers, σ_1, σ_2, and ν are positive real numbers, and ω is a negative real number. The difference between parameters σ_1 and σ_2 reflects the different travel impedance for domestic and international trips (another option would be to considered different values for α in the demand function)

The cost for the airports (in constraints 6) is given by the sum of a fixed cost, the power of the utilization rate, and the power of capacity (the last parcel, not considered in the model formulation presented previously, was included to promote the 'hubbing' effect of the most important connecting airports, and also, only the airports of Frankfurt, München and Düsseldorf were defined as hub airports). Therefore, the cost function can be rewritten as follows:

$$C_2\left(\frac{w_n}{z_n}, z_n\right) = \tau + \theta\left(\frac{w_n}{z_n}\right)^{\rho 1} {z_n}^{\rho 2}, \ \forall j \in \boldsymbol{N} \qquad (23)$$

where τ, θ, and ρ_1 are positive real numbers, and ρ_2 is a negative real number.

4.4 Estimation results

The values obtained for the calibration parameters, as well as their initial ranges, are presented in Table 49. The results shown were obtained considering the values for the parameters of Nelder-Mead algorithm recommended in Conn et al. (2009) ($\alpha^R = 1$, $\alpha^E = 2$, $\alpha^{OC} = 0.5$, $\alpha^{IC} = -0.5$, and $\alpha^S = 0.5$). The traffic flows simulated with these parameter values and the observed traffic flows are compared in Figure 34 for the metropolitan areas. The correlation coefficient between modeled and observed traffic flows is 0.87. These results show that, overall, our model represents the traffic flows at the metropolitan areas in a quite satisfactory manner. However, a closer look shows that the model tends to overestimate the traffic flows for the metropolitan areas with lower volumes of traffic. The airport network and modeled air traffic flows for the average day of 2008 is given in Figure 35, and the corresponding airport information is given in Table 50 (only the metropolitan areas of Germany and domestic flight legs are represented).

The total system throughput, accounting for the total number of enplanements within Gernany, is 309.9×10^3 pax/day. All metropolitan areas have enough capacity to serve all demand, but 9 operate at utilization rates greater than 80% (which is a value commonly assumed to indicate the occurrence of significant airport congestion problems, de Neufville and Odoni 2003). The corresponding road and rail networks are given in Figure 36 and Figure 37, respectively. The total (domestic and international) link traffic for the car and train modes are 185.5×10^3 and 37.3×10^3 pax/day, respectively.

Table 49 – Initial range and values for the parameters

λ	λ^{min}	λ^{max}	Value
α	10.0	100.0	25.0
μ	1	1.5	0.520
β_1	1	2	0.780
β_2	1	2	0.800
σ_1	1	10	8.00
σ_2	1	10	8.80
ν	0	1	0.51
ω	-0.2	0	-0.120
τ	0	30	11.43
θ	0.01	0.1	0.020
ρ_1	1	3	1.590
ρ_2	-1	-0.1	-0.06
γ	0.01	0.05	0.05

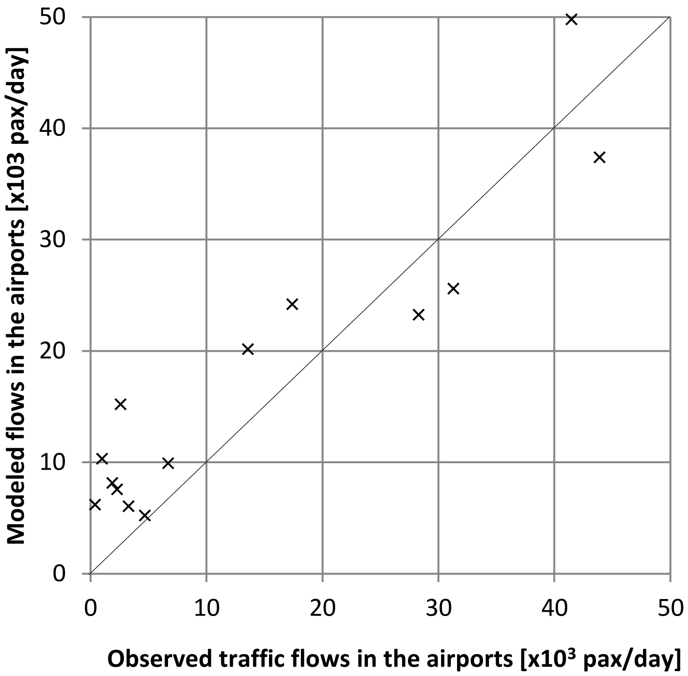

Figure 34 – Estimation results: comparison between modeled and observed traffic flows in the metropolitan areas

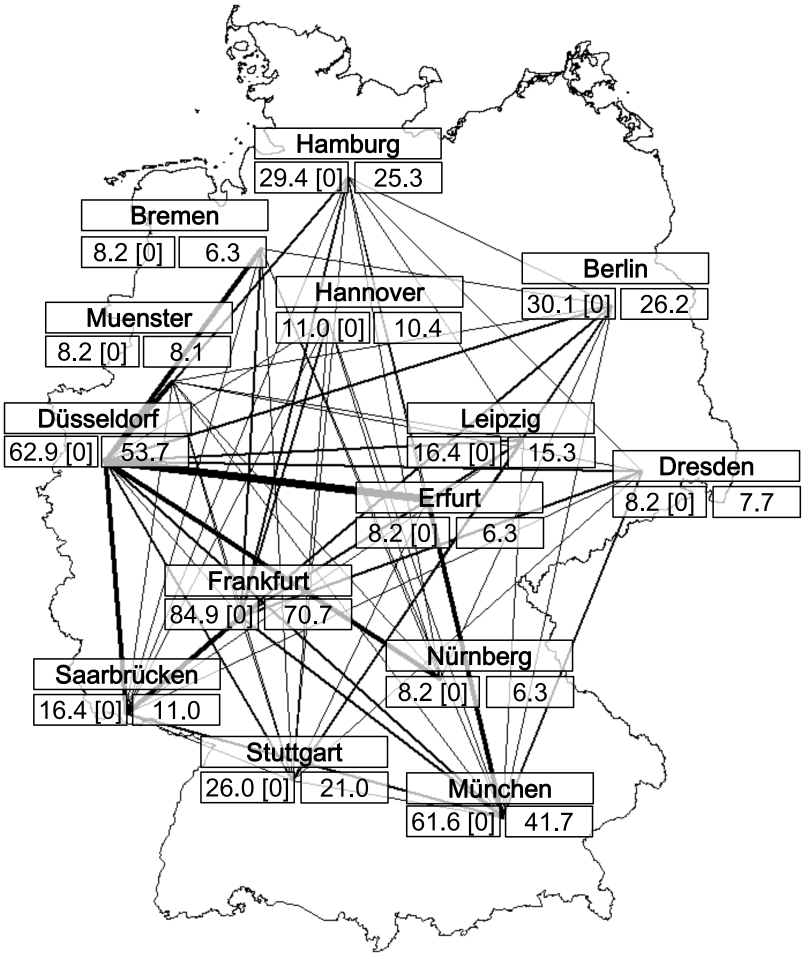

Figure 35 – Airport network for the estimated parameters

Table 50 – Model results for the estimated parameters

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (EUR/pax)	Tax (EUR/pax)
Hamburg	29.4	25.3	86	30.9	0.0
Hannover	11.0	10.4	94	35.4	0.0
Bremen	8.2	6.3	77	29.0	0.0
Düsseldorf	62.9	53.7	85	29.8	0.0
Frankfurt	84.9	70.7	83	28.8	0.0
Stuttgart	26.0	21.0	81	29.1	0.0
Nürnberg	8.2	6.3	77	28.9	0.0
München	61.6	41.7	68	24.1	0.0
Berlin	30.1	26.2	87	31.3	0.0
Saarbrücken	16.4	11.0	67	25.0	0.0
Muenster	8.2	8.1	98	37.4	0.0
Leipzig	16.4	15.3	93	34.3	0.0
Dresden	8.2	7.7	94	35.7	0.0
Erfurt	8.2	6.3	77	29.1	0.0

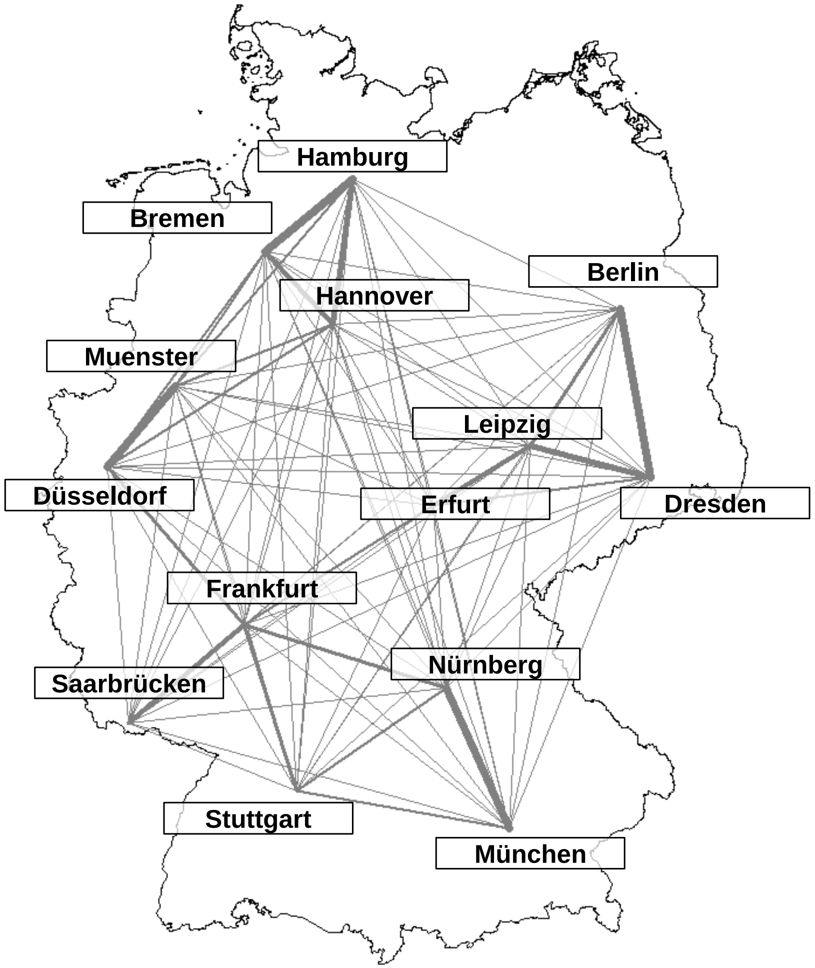

Figure 36 – Road network for the estimated parameters

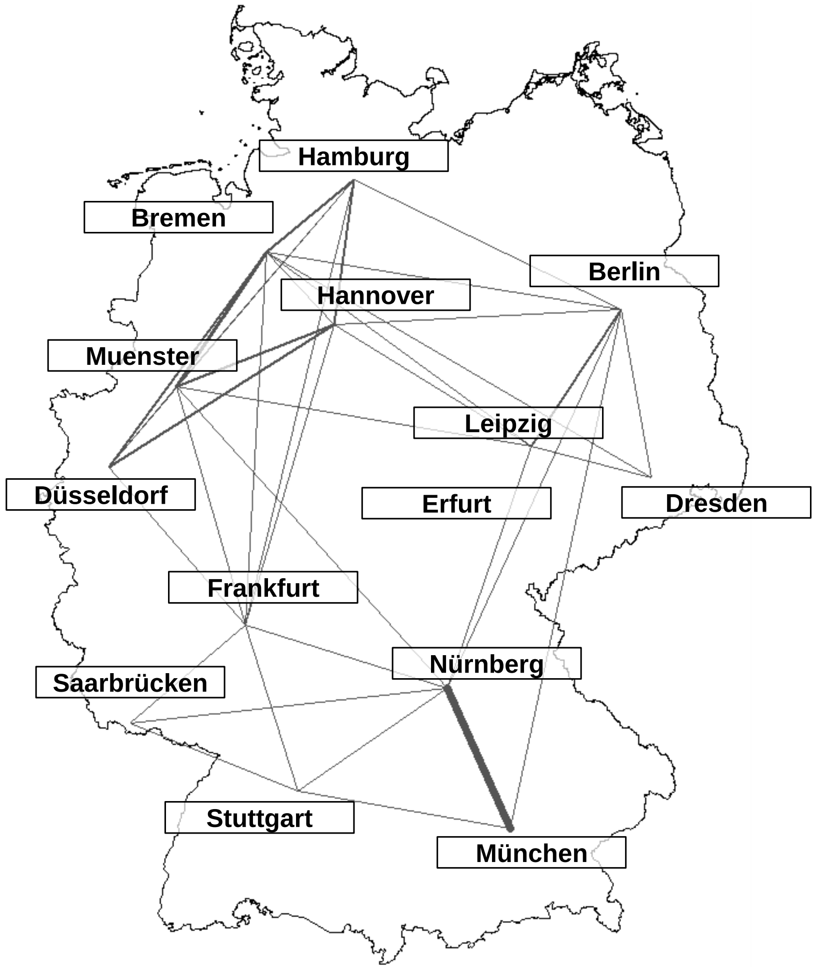

Figure 37 – Rail network for the estimated parameters

5. Network Evolution

In this section, we analyze the long-term evolution of the main airport network of Germany. This is accomplished by comparing the performance of the airport network for a peak day of operations in 2008 ("current network") with the expected performance of the airport network for an equivalent day in 2030 depending on the budget applied in expansion actions ("future network").

In the following sub-sections we discuss the performance of the current network, describe the possible expansion actions applicable to the metropolitan areas and respective costs, and assess the performance of the future network as a function of the budget available.

5.1 Current network

As stated above, the performance of the current network was analyzed for a peak day of operations of 2008. Since the statistical calibration of model parameters was carried out using data for the average day of operations in 2008, the demand function for trips with a given origin airport, j, was multiplied by a peaking factor τ_j (>1). Due to the lack of available data, a peaking factor of 1.2 was admitted for all airports (i.e., traffic in the peak day under consideration is 20% higher than in the average day of operations).

For the peak day of operations in 2008, the metropolitan areas of Hannover, Bremen, Muenster, Leipzig, Dresden and Erfurt would suffer from severe lack of capacity, and congestion taxes would have to be charged in order to regulate the utilization of capacity (avoiding excess demand situations). In addition, the metropolitan areas of

Hamburg, Düsseldorf, Frankfurt, Stuttgart, Nürnberg, Berlin and Saarbrücken would present congestion problems (since utilization rate would exceed 80%). The airport network is given in Figure 38, and the corresponding airport information is given in Table 51. The total system throughput is 325.4×10^3 pax/day. The total link traffic for the car and train modes are 227.8 and $42.8\text{x}10^3$ pax/day, respectively.

5.1 Expansion actions

The possible expansion actions to apply to the metropolitan areas were assumed to consist of the addition or reconfiguration of runways, as runways are generally the most constraining elements of an airport. The following rules were considered: (i) existing runways at some airports can be improved (if their length is about 2,000 m or below), increasing capacity by 10×10^3 pax/day; (ii) the addition of a medium-spaced parallel runway to an independent runway increases capacity by 10×10^3 pax/day; (iii) the addition of an independent runway to the existing runway layout increases capacity by 20×10^3 pax/day; and (iv) a new airport can be built in all metropolitan areas, thus making it possible to overcome the difficulty of expanding existing airports often located in consolidated urban areas. It is worth noting here that the capacity increase values indicated above are not intended to match the specific conditions of each airport; they are rather hypothetical figures derived from similar projects.

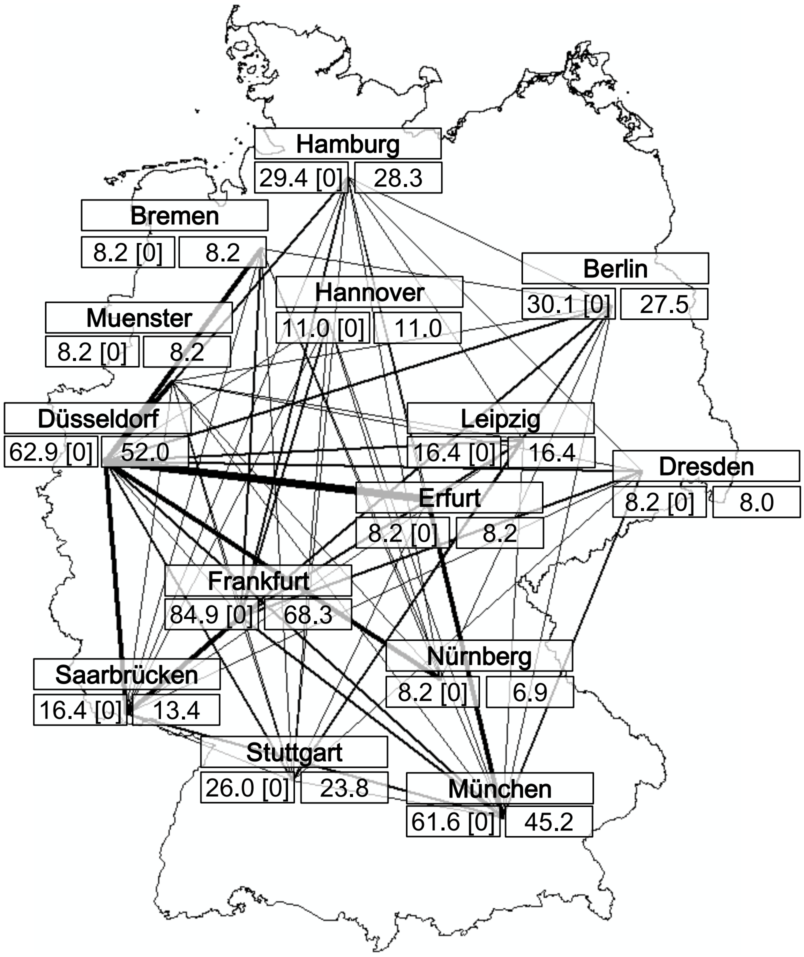

Figure 38 – Current airport network

Table 51 – Model results for the current airport network

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (EUR/pax)	Tax (EUR/pax)
Hamburg	29.4	28.3	96	34.7	0.0
Hannover	11.0	11.0	100	37.6	5.5
Bremen	8.2	8.2	100	38.3	1.1
Düsseldorf	62.9	52.0	83	28.9	0.0
Frankfurt	84.9	68.3	80	27.8	0.0
Stuttgart	26.0	23.8	91	33.0	0.0
Nürnberg	8.2	6.9	84	31.8	0.0
München	61.6	45.2	73	25.9	0.0
Berlin	30.1	27.5	91	32.8	0.0
Saarbrücken	16.4	13.4	81	29.9	0.0
Muenster	8.2	8.2	100	38.1	3.2
Leipzig	16.4	16.4	100	37.0	10.0
Dresden	8.2	8.0	98	37.3	8.5
Erfurt	8.2	8.2	99	38.1	3.0

With the closure of Berlin-Tegel (TXL) in 2012, the metropolitan area of Berlin will only served by an airport, Berlin-Brandenburg (BER) (former Berlin-Schönefeld SXF). This airport will have a new independent runway by the time it opens (hence, it will have two independent parallel runways). Therefore, the capacity of the metropolitan area of Berlin is assumed to increase from 30.1 to $40x10^3$ pax/day.

The airport capacity increases (in enplanements per day) corresponding to the possible expansion actions applicable to the airports are shown in Table 52. The airport capacity increases applicable to the metropolitan areas, obtained by combining the airport capacity increases applicable to the airports, are shown in Table 53. The cost of the capacity increases, which were obtained assuming that the improvement of an existing runway costs 4 billion EUR, the construction of a new single runway airport costs 8 billion EUR, and the addition of a medium-spaced parallel runway and an independent parallel runway, costs, respectively, 2 and 6 billion EUR, are presented in Table 54.

Table 52 – Possible airport capacity increases in the airports (10^3 enplanements/day)

Metro. area	Airport	Improve runway	+ indep. runway (new airport)	+ medium spaced parallel runway	+ indep. runway	+ medium spaced parallel runway	+ medium spaced parallel runway
Hamburg	HAM	-	-	-	-	-	-
	LBC	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Hannover	HAJ	10	-	-	30	40	50
	New airport	-	20	30	40	50	60
Bremen	BRE	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Düsseldorf	DUS	-	-	-	-	-	-
	CGN	-	-	-	20	30	40
	DTM	10	-	20	-	-	-
	NRN	10	-	20	-	-	-
	New airport	-	20	30	40	50	60
Frankfurt	FRA	-	-	-	-	20	30
	HHN	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Stuttgart	STR	-	-	10	20	30	40
	FKB	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Nürnberg	NUE	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
München	MUC	-	-	-	-	10	20
	New airport	-	20	30	40	50	60
Berlin	TXL	-	-	-	-	-	-
	SXF	-	-	-	-	10	20
	New airport	-	20	30	40	50	60
Saarbrücken	SCN	10	-	20	30	40	50
	ZQW	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Muenster	FMO	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Leipzig	LEJ	10	-	-	20	30	40
	New airport	-	20	30	40	50	60
Dresden	DRS	10	-	20	30	40	50
	New airport	-	20	30	40	50	60
Erfurt	ERF	10	-	20	30	40	50
	New airport	-	20	30	40	50	60

Table 53 – Possible airport capacity increases in the metropolitan areas (10^3 enplanements/day)

Metro. Area	Expansion level									
	1	2	3	4	5	6	7	8	9	10
Hamburg	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**
Hannover	10	30	40	50	**70**	**80**	**90**	**100**	-	-
Bremen	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**
Düsseldorf	20	30	40	50	60	70	80	**100**	**110**	**120**
Frankfurt	20	30	40	50	60	70	80	**100**	**110**	**120**
Stuttgart	10	20	30	40	50	60	70	80	90	**110**
Nürnberg	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**
München	10	20	**40**	**50**	**60**	**70**	**80**	-	-	-
Berlin	10	20	**40**	**50**	**60**	**70**	**80**	-	-	-
Saarbrücken	10	20	30	40	50	60	70	80	90	100
Münster	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**
Leipzig	10	20	30	40	**60**	**70**	**80**	**90**	**100**	-
Dresden	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**
Erfurt	10	20	30	40	50	**70**	**80**	**90**	**100**	**110**

Table 54 – Cost of airport capacity increases (EUR bn)

Metro. Area	Expansion level									
	1	2	3	4	5	6	7	8	9	10
Hamburg	4	10	13	16	18	26	28	32	34	36
Hannover	4	13	16	18	26	28	32	36	-	-
Bremen	4	10	13	16	18	26	28	32	34	36
Düsseldorf	9	12	14	18	24	28	34	42	44	48
Frankfurt	6	8	12	18	21	24	26	34	36	40
Stuttgart	6	9	12	14	18	24	27	30	32	40
Nürnberg	4	10	13	16	18	26	28	32	34	36
München	10	20	28	30	34	36	38	-	-	-
Berlin	12	14	22	24	28	30	80	-	-	-
Saarbrücken	4	10	13	16	18	22	28	31	34	36
Münster	4	10	13	16	18	26	28	32	34	36
Leipzig	4	13	16	18	26	28	32	34	36	-
Dresden	4	10	13	16	18	26	28	32	34	36
Erfurt	4	10	13	16	18	26	28	32	34	36

5.2 Network evolution as a function of expenditure

The future network was obtained through the optimization model for the reference peak day of operations in 2030 as a function of three budget values: *b*=0 (no expansion budget), *b*=50 bn EUR, and *b*=100 bn EUR. The demand to satisfy was defined assuming that population will continue to evolve in the various metropolitan areas according to the same patterns as between 1991 and 2008. The connecting traffic flows with origin and destination in airports not included in the network were considered to increase by 2.8%, which is consistent with the projections of EUROCONTROL (2010b) ('most-likely' scenario). The travel cost by car and train were assumed to keep unchanged over time. This means that the rail and road networks are not capacity constrained, no new links will be built, and the service frequency of the rail transport will not change.

5.2.1 No Expansion Budget

For the demand scenario considered (same demand function as in 2008, with the population forecast for 2030), and assuming that the airport network would remain the same (*b*=0), the metropolitan areas of Hamburg, Hannover, Bremen, Frankfurt, Nürnberg, Münster, Leipzig, Dresden and Erfurt would not have enough capacity to serve all demand, forcing the transport authority to charge congestion taxes in order to regulate the utilization of capacity (Hannover, Bremen, Münster, Leipzig, Dresden and Erfurt already presented capacity shortage problems in 2008) (Figure 39 and Table 55). In addition, the metropolitan areas of Düsseldorf, Stuttgart, München and Saarbruckën would manifest congestion problems (utilization rate would exceed 80%). The number of daily enplanements in the network would rise to 535.8×10^3, corresponding to an increase of about 13.6% relative to the current network. Some traffic would be diverted to the road and rail networks as a result of the congestion problems at the airport network – the total traffic in the road and rail networks would be 244.6 and 44.0×10^3 pax/day, respectively, which correspond to increases of 7.4% and 2.8% relative to the current network.

5.2.2 Expansion budget of 50 billions EUR

Assuming the 50 bn EUR budget for the expansion of the existing airport network, the capacity of seven metropolitan areas would be increased: Münster, Hannover and Erfurt would be expanded in one capacity level with the improvement of one runway in the airports of FMO, HAJ and ERF, respectively, increasing their capacity by $10\text{x}10^3$ pax/day; Düsseldorf would also be expanded one level through the construction of an independent runway in Koln-Bonn (CGN), increasing its capacity by $20\text{x}10^3$ pax/day; and Nürnberg, Dresden and Stuttgart would be expanded in two levels, through the improvement of one runway and the construction of a medium-spaced parallel runway in NUE and DRS, and the construction of an independent parallel runway in STR (increasing their capacity by $30\text{x}10^3$ pax/day) – see Figure 40 and Table 56. With these improvements in the airport network, the metropolitan areas of Hamburg, Bremen, Nürnberg, Münster, Leipzig, Dresden and Erfurt would then have enough capacity to serve all demand. On the other hand, for the cases of Frankfurt and Hannover, the enhancements would not be enough to satisfy all demand, and, consequently, congestion taxes of 1.0 and 3.7 EUR/pax, respectively, would have to be charged to each passenger in order to regulate demand. Total throughput would rise to 595.8×10^3 pax/day, corresponding to an increase of about 26.3% relative to the current network. The total traffic in the road and rail networks would decrease, respectively, to 182.8×10^3 pax/day (-19.8%) and 29.7×10^3 pax/day (-30.6%).

5.2.3 Expansion budget of 100 billions EUR

With a budget of 100 bn EUR, the airport network should be further improved as follows: Bremen and Leipzig would both be expanded in one capacity level, through improvements of one runway at BRE and LEJ (increasing their capacity by $10 \text{x} 10^3$ pax/day); Hannover, Erfurt and Düsseldorf (which had been expanded one capacity level for a budget of 50 bn EUR) would be expanded to the second capacity level, through the construction of an independent parallel runway in HAJ (additional capacity of $20 \text{x} 10^3$ pax/day), and through the construction of a medium-spaced parallel runway in ERF and CGN (additional capacity of $10 \text{x} 10^3$ pax/day); Dresden (which had been previously expanded two capacity levels) would be expanded to the third capacity level through the construction of an independent parallel runway in DRS (additional capacity of $10 \text{x} 10^3$ pax/day), and Frankfurt would be expanded in four capacity levels through the construction of two medium-spaced parallel runways in Frankfurt-International (FRA) and by the improvement of one runway and the construction of a medium-spaced parallel runway in Frankfurt-Hahn (HHN) (thus increasing the aggregate airport capacity of Frankfurt by $50x10^3$ pax/day) – see Figure 41 and Table 57. With the changes performed to the airport network, all metropolitan areas would have enough capacity to satisfy demand. However, the congestion problems at some metropolitan areas (Hamburg, Nürnberg, München and Saarbrücken) would persist. Total throughput would rise to 637.6×10^3 pax/day, corresponding to an increase of about 46.6% relative to the current network, and 19% relatively to the "no expansion" network. The total traffic in the road and rail networks would be 168.2 and 30.1×10^3 pax/day, corresponding to decreases of 26.2% and 29.7% relative to the current network.

6. Conclusion

This chapter described a study which purpose was to provide some insights into the long-term capacity needs of the main airport network of Germany. The study was based on an optimization model aimed at assisting aviation authorities in their strategic decisions regarding the expansion of airport networks. The model looks to a set of metropolitan areas, which can either be served by airports/multi-airport systems, or not, and determines the expansion actions to apply to the metropolitan areas in order to maximize total system throughput for a given budget. The model takes into account the impact of airport congestion and the complementarity/competition between air travel and land travel modes on travel cost and demand for air transportation. Expansion actions consist of the expansion of existing airports (e.g. through the addition of new runways or the reconfiguration of existing runways) and the construction of new airports (however, it was not considered in this study the possibility of building a new airport in metropolitan areas currently not served by airport).

The study focused on the 14 metropolitan areas served by international airports. The horizon year we considered was 2030. The results we obtained with respect to a reference peak day of operations in that year reveal that, if nothing is done, 9 metropolitan areas will not have enough capacity to satisfy all demand (and other 4 will present congestion problems). Because of the capacity shortage at some metropolitan areas, some traffic would be diverted to the road and rail networks (the total traffic by car and train would increase by 7.4% and 2.8% relative to the current network).

We have also analyzed the best way of improving the existing airport network with budgets of 50 billion and 100 billion EUR. If a 50 billion EUR budget was provided for the expansion of the airport network, the study points out that the capacity of 7 metropolitan areas (Münster, Hannover, Erfurt, Düsseldorf, Nürnberg, Dresden and Stuttgart) should be increased through the expansion of 9 airports. With these improvements in the network, total system throughput would increase by about 26.3% relatively to the current network. The total traffic in the road and rail networks would decrease, respectively, by 19.8% and 30.6%. With a budget of 100 billion EUR, the airports in the metropolitan areas of Hannover, Erfurt, Düsseldorf and Dresden would be further improved, and Bremen, Leipzig, and Frankfurt would also receive additional capacity. With these improvements in the airport network, total system throughput would increase by about 46.6%, and the total traffic in the road and rail networks would decrease by 26.2% and 29.7% relative to the current network.

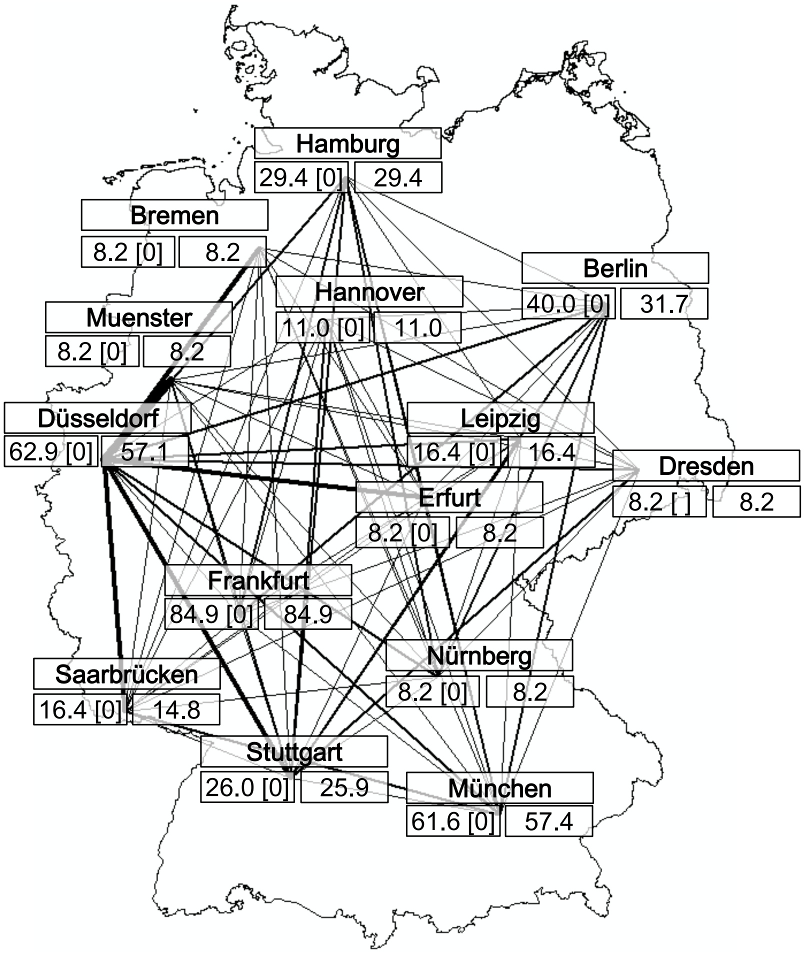

Figure 39 – Airport network in 2030 for *b*=0

Table 55 – Traffic and costs for the airports in 2030 for *b*=0

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (EUR/pax)	Tax (EUR/pax)
Hamburg	29.4	29.4	100	36.1	3.6
Hannover	11.0	11.0	100	37.6	12.9
Bremen	8.2	8.2	100	38.1	3.7
Düsseldorf	62.9	57.1	91	31.7	0.0
Frankfurt	84.9	84.9	100	34.6	3.5
Stuttgart	26.0	25.9	99	36.1	0.0
Nürnberg	8.2	8.2	100	38.1	2.2
München	61.6	57.4	93	32.6	0.0
Berlin	40.0	31.7	79	28.2	0.0
Saarbrücken	16.4	14.8	90	33.1	0.0
Muenster	8.2	8.2	100	38.1	9.8
Leipzig	16.4	16.4	100	37.0	14.9
Dresden	8.2	8.2	100	38.1	2.5
Erfurt	8.2	8.2	100	38.1	0.3

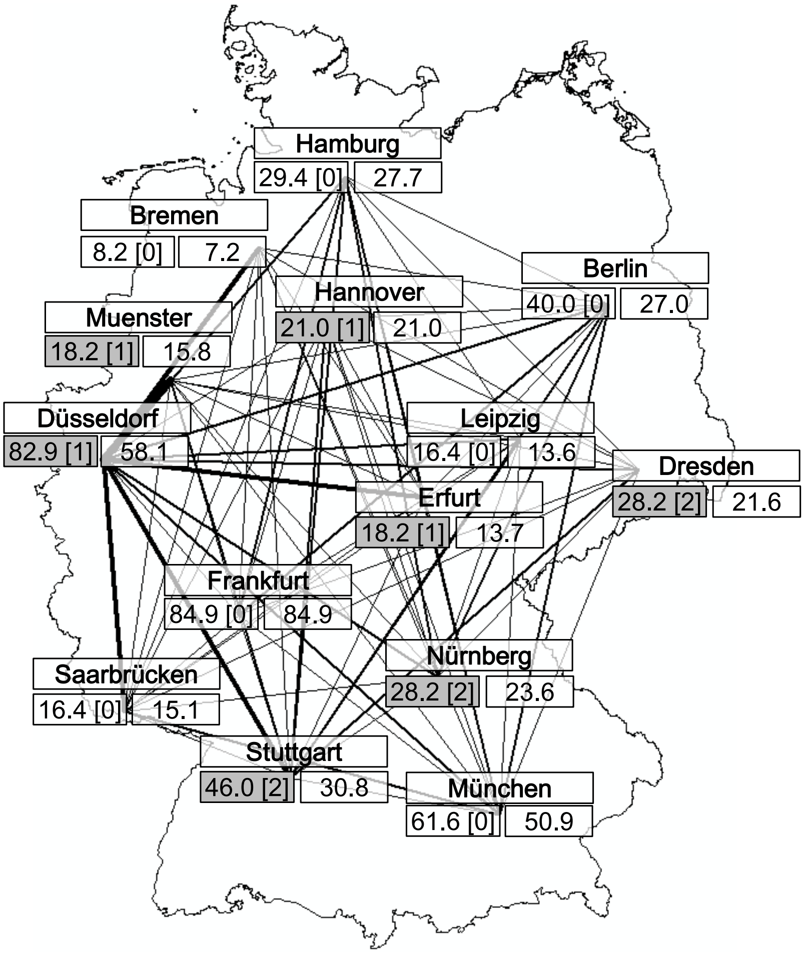

Figure 40 – Airport network in 2030 for *b* = EUR 50 bn

Table 56 – Traffic and costs for the airports in 2030 for *b* = EUR 50 bn

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (EUR/pax)	Tax (EUR/pax)
Hamburg	29.4	27.7	94	33.9	0.0
Hannover	21.0	21.0	100	36.6	3.7
Bremen	8.2	7.2	87	33.0	0.0
Düsseldorf	82.9	58.1	70	24.6	0.0
Frankfurt	84.9	84.9	100	34.6	1.0
Stuttgart	46.0	30.8	67	24.2	0.0
Nürnberg	28.2	23.6	84	30.1	0.0
München	61.6	50.9	83	28.9	0.0
Berlin	40.0	27.0	67	24.4	0.0
Saarbrücken	16.4	15.1	92	33.9	0.0
Muenster	18.2	15.8	87	31.7	0.0
Leipzig	16.4	13.6	83	30.4	0.0
Dresden	28.2	21.6	76	27.6	0.0
Erfurt	18.2	13.7	75	27.6	0.0

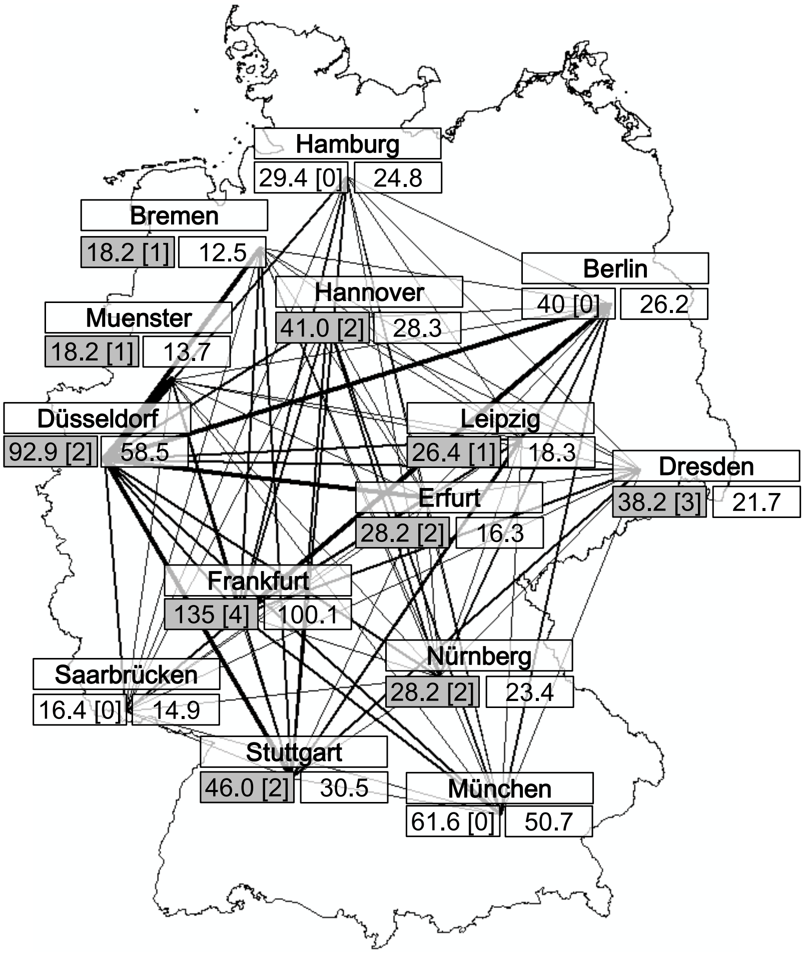

Figure 41 – Airport network in 2030 for *b* = EUR 100 bn

Table 57 – Traffic and costs for the airports in 2030 for *b* = EUR 100 bn

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (EUR/pax)	Tax (EUR/pax)
Hamburg	29.4	24.8	84	30.3	0.0
Hannover	41.0	28.3	69	24.9	0.0
Bremen	18.2	12.5	68	25.4	0.0
Düsseldorf	92.9	58.5	63	22.5	0.0
Frankfurt	134.9	100.1	74	25.5	0.0
Stuttgart	46.0	30.5	66	24.0	0.0
Nürnberg	28.2	23.4	83	29.8	0.0
München	61.6	50.7	82	28.8	0.0
Berlin	40.0	26.2	65	23.8	0.0
Saarbrücken	16.4	14.9	91	33.3	0.0
Muenster	18.2	13.7	75	27.7	0.0
Leipzig	26.4	18.3	69	25.3	0.0
Dresden	38.2	21.7	57	21.4	0.0
Erfurt	28.2	16.3	58	21.8	0.0

The results obtained show that the model upon which the study was based can be useful to support analyses of the evolution of airport networks and to provide insights into the best way of expanding them. However, in order to use the outcomes of the model for real-world applications, the calibration of the model parameters and the definition of the possible expansion actions applicable to the airports must be made in a more comprehensive manner. In addition, the model must be used taking into account possible improvements in efficiency and technology in the future, which may lead to substantial capacity increases, thus reducing the need for capacity expansion actions.

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Chapter 6

Dynamic and Stochastic Models for the Expansion of Airport Networks: Formulation and Solution Algorithms

1. Introduction

The problem faced by aviation authorities in their strategic decisions regarding the expansion of airport networks is known as the airport network capacity expansion problem. The problem is to find the best improvements to implement for an airport network in order to cope with future demand in the best possible way, while complying with a given budget. Chapter 2 presented an optimization model for dealing with the problem. The model looks to a set of population centers served by airports/multi-airport systems, and determines the expansion actions to apply to the centers in order to maximize total system throughput for a given budget, taking into account the capacity of the airports upon travel costs and demand for air travel.

The model presented in Chapter 2 can be characterized as both static and deterministic, as it takes constant, known quantities as inputs (e.g. demand and travel costs) and derive a single solution to be implemented at one point in time. Such static and deterministic formulation does not capture some important aspects involved in airport capacity expansion problems, as the strategic nature of the planning process requires models to take dynamic and uncertainty issues into account (de Neufville and Odoni 2003). Since the expansion and construction of airports are costly and difficult to reverse, these infrastructures are expected to keep a good performance for an extended time period. During the time when design decisions are in effect, any of the parameters of the problem may fluctuate widely, and parameter estimates may also be inaccurate due to poor measurements. Furthermore, decision makers must not only select robust solutions which will effectively cope with changing demand over time, but must also consider the timing of expansion actions over the long run.

The purpose of this chapter is to expand the model presented in Chapter 2 by considering explicitly the dynamic and uncertainty issues inherent in airport capacity expansion problems. Section 2 addresses the former, looking at a dynamic and deterministic version of the model, in which the goal is to find the best schedule to perform the improvements in the airport network, for the demand and budget available in the different time periods. Section 3 presents a stochastic and static version of the model, which considers different scenarios regarding future demand, and determines the expansion actions to apply to the airport network in order to minimize expected regret across the scenarios under consideration. The third model, presented in Section 4, considers both dynamic and stochastic characteristics of the two previous models, and determines the best schedule to perform the improvements in the airport network in order to minimize expected regret (for a brief overview on this subject, the reader is referred to Appendix A, which presents a formulation of the dynamic and stochastic *p*-median model).

2. Dynamic and deterministic model

The shortcomings of static formulations have been recognized long ago in the optimization literature, such as the facility location and the multi-region capacity expansion literature. Hence, a growing number of studies have been focusing on dynamic approaches. Dynamic approaches seek solutions which will effectively serve changing demand over time, and consider the timing of facility openings and/or expansions over the design period under consideration. On facility location theory, Ballou (1968) presented the first mathematical formulation for the dynamic single facility location problem, and a solution approach for solving the model based on a myopic scheme which uses a series of static deterministic optimal solutions to solve the dynamic problem. Later, this solution approach for solving the model was proven to be sub-optimal in Sweeney and Tatham (1976). Scott (1971) focused on the dynamic multiple facility location-allocation problem and developed a sub-optimal myopic approach to solve the model. Tapiero (1971) extended the study of Scott so as to include capacity constraints and shipping costs in the objective-function. As for the multi-region capacity expansion problem, the first known study to address the problem was due to Sheppard (1974), who presented a variety of models to determine not only the location of multiple facilities, but also the size of the facilities and the timing of facility construction and expansion.

Some dynamic approaches developed for dealing with facility location and multi-region capacity expansion problems share some aspects with the dynamic airport network capacity expansion problem, and so does their mathematical formulation. The following subsections discuss a formulation for the dynamic and deterministic airport network capacity expansion model and describe a heuristic solution method used to solve it. The type of results that can be expected from the application of the model is then illustrated for a small-size, hypothetical airport network.

2.1 Model formulation

The dynamic and deterministic airport network capacity expansion model uses the following notation:

Sets:

$\boldsymbol{N}$ - set of population centers or airports

$\boldsymbol{T}$ - set of time periods

$\boldsymbol{N}_{jkr}$ - set of centers included in route r connecting centers j and k

$\boldsymbol{L}$ - set of flight legs

$\boldsymbol{L}_j$ - set of legs with start point in center *j*

$\boldsymbol{L}_{jkr}$ - set of legs included in route *r* connecting centers *j* and *k*

$\boldsymbol{R}_{jk}$ - set of routes connecting centers *j* and *k*

$\boldsymbol{R}_l$ - set of routes containing flight leg *l*

$\boldsymbol{M}_j$ - set of expansion actions applicable to center *j*

Parameters:

p^t_j - population of center *j* in time period *t*

d_{jk} - travel distance between centers *j* and *k*

s_j - initial airport capacity of center *j*

g_{jm} - capacity increase in center *j* due to the application of expansion action *m*

e_{jm} - cost of applying expansion action *m* to center *j*

ϕ^t_{jk} - modal split factor between centers *j* and *k* in time period *t*

b^t - budget available for expansion actions in time period *t*

Decision variables:

q^t_{jk} - O-D traffic flow between centers *j* and *k* in time period *t*

w^t_j - traffic flow in center *j* in time period *t*

u^t_l - traffic flow on leg *l* in time period *t*

v^t_{jkr} - traffic flow in route *r* connecting centers *j* and *k* in time period *t*

c^t_{jk} - average travel cost between centers *j* and *k* in time period *t*

c^t_{jkr} - travel cost for route r connecting centers j and k in time period t

z^t_j - final capacity of center j in time period t

x^t_j - congestion tax to apply in center j in time period t

y^t_{jm} - binary variable equal to 1 if expansion action m is applied to center j in time period t, and equal to 0 otherwise.

The variables and parameters related with traffic flows on the legs and routes are measured in number of passengers (per day), and the ones related with airport capacities and traffic flows in the centers are defined in enplanements. Travel costs are defined in \$/passenger.

Using the notation above, the mathematical formulation of the model is as follows:

$$\max \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{t \in \boldsymbol{T}} q^t_{jk} \tag{1}$$

subject to:

$$z^t_j \geq w^t_j, \quad \forall j \in \boldsymbol{N}, \quad \forall t \in \boldsymbol{T} \tag{2}$$

$$z^t_j = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm} \, y^t_{jm}, \quad \forall j \in \boldsymbol{N}, \quad \forall t \in \boldsymbol{T} \tag{3}$$

$$\sum_{m \in \boldsymbol{M}_j} y^t_{jm} \leq 1, \quad \forall j \in \boldsymbol{N}, \quad \forall t \in \boldsymbol{T} \tag{4}$$

$$\sum_{m \in \boldsymbol{M}_j} g_{jm} y^t_{jm} \geq \sum_{m \in \boldsymbol{M}_j} g_{jm} y^{t-1}_{jm}, \quad \forall j \in \boldsymbol{N}, \quad \forall t \in \boldsymbol{T} \mid t > 1 \tag{5}$$

$$\sum_{j \in N}\sum_{m \in \boldsymbol{M}_j} e_{jm} y_{jm}^t \leq b^t, \ \ \forall t \in \boldsymbol{T} \tag{6}$$

$$q_{jk}^t = Q\left(p_j^t, p_k^t, \phi_{jk}^t, c_{jk}^t\right), \ \ \forall j,k \in \boldsymbol{N}, \ \ \forall t \in \boldsymbol{T} \tag{7}$$

$$v_{jkr}^t = \frac{e^{-\gamma c_{jkr}^t}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkp}^t}} q_{jk}^t, \ \ \forall j,k \in \boldsymbol{N}, \ \ \forall r \in \boldsymbol{R}_{jk}, \ \ \forall t \in \boldsymbol{T} \tag{8}$$

$$u_l^t = \sum_{j \in \boldsymbol{N}}\sum_{k \in \boldsymbol{N}}\sum_{r \in \boldsymbol{R}_l} v_{jkr}^t, \ \ \forall l \in \boldsymbol{L}, \ \ \forall t \in \boldsymbol{T} \tag{9}$$

$$w_j^t = \sum_{l \in \boldsymbol{L}_j} u_l^t, \ \ \forall j \in \boldsymbol{N}, \ \ \forall t \in \boldsymbol{T} \tag{10}$$

$$c_{jkr}^t = \sum_{l \in \boldsymbol{L}_{jkr}} C_1\left(d_l, u_l^t\right) + \sum_{n \in \boldsymbol{N}_{jkr}} \left[C_2\left(\frac{w_n^t}{z_n^t}\right) + x_n^t \right], \ \ \forall j,k \in \boldsymbol{N}, \ \ \forall r \in \boldsymbol{R}_{jk}, \ \ \forall t \in \boldsymbol{T} \tag{11}$$

$$c_{jk}^t = \frac{\sum_{r \in \boldsymbol{R}_{jk}} c_{jkr}^t v_{jkr}^t}{q_{jk}^t}, \ \ \forall j,k \in \boldsymbol{N}, \ \ \forall t \in \boldsymbol{T} \tag{12}$$

$$y_{jm}^t \in \{0,1\}, \ \ \forall j \in \boldsymbol{N}, \ \ \forall m \in \boldsymbol{M}_j, \ \ \forall t \in \boldsymbol{T} \tag{13}$$

The objective function (1) of the model expresses the maximization of total system throughput, as measured by the total number of enplanements made within the airport network across the set of time periods under consideration (maximization of “demand coverage”).

Constraints (2) establish that the airport capacity of the centers must be able to accommodate the traffic flow in all time periods.

Constraints (3) state that the capacities of the centers in each time period are given by the sum of their initial capacities and the capacity increase due to the expansion action applied in that time period.

Constraints (4) ensure that at most one expansion action will be applied for each center and time period.

Constraints (5) state that the airport capacity of each center can be increased from a time period to the next, or kept unchanged (it is not possible to decrease capacity).

Constraints (6) guarantee that the total expenditure will comply with the budget available for expansion actions in each time period (the budget constraint can also be defined as a function of an aggregate budget for all time periods).

Constraints (7) are the O-D demand functions relating the traffic flows between each pair of centers in each time period with their size, with a modal split factor reflecting the competition from other modes connecting the centers (which may differ among time periods as land transportation infrastructures may be improved), and with the average (generalized) travel cost between the centers.

Constraints (8) assign the O-D traffic flows to flight routes in each time period as a function of the average travel cost through a logit model.

Constrains (9) calculate the traffic flow in each flight leg in each time period by summing the traffic flows in the routes containing those legs.

Constrains (10) compute the enplanements at the centers (airports) in each time period by summing the traffic flows in the legs with start point in those centers.

Constraints (11) compute the travel cost for each route in each time period. This cost is calculated by summing the cost for the legs and the cost for the airports included in that route. The cost for the legs (first term) is assumed to increase with travel distance, and, because of economies of scale, to decrease with traffic flow. The cost for the airports (second term) is assumed to increase with the utilization rate because congestion makes airport operations more expensive and time-consuming. Therefore,

$$\partial C_1 / \partial d_l > 0, \partial C_1 / \partial u_l^t < 0, \text{ and } \partial C_2 / \partial \left(\frac{w_n^t}{z_n^t} \right) > 0$$

The airport cost may include a congestion tax levied by the aviation authority in order to regulate the utilization of airport capacity in case of excess demand.

Constraints (12) calculate the average (generalized) travel cost for each pair of centers in each time period by summing the cost for the routes connecting the centers weighted by the respective traffic flow and then dividing by the total traffic flow.

Finally, constraints (13) define the capacity expansion variables as binary (all other decision variables are non-negative real numbers).

2.2 Solution approach

The model presented is quite difficult to solve, because of its dynamic nature, and also as it combines the complexity of non-linear and mixed integer optimization models. A heuristic solution method based on the one presented in Chapter 3 was developed to solve the model. This method comprises two iterative procedures: (1) determination of capacity expansion actions to apply to the airport network (candidate solutions); (2) determination of equilibrium flows and travel costs within the airport network. The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the airports consistent with the budget available in each time period, and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The second procedure (lower-level) procedure determines the equilibrium traffic flows and costs in each time period for the candidate solutions. It also determines the congestion taxes to apply in order to cancel out excess demand situations that might occur in some airport(s). Candidate solutions are encoded in $|\boldsymbol{T}|$ strings of $|\boldsymbol{N}|$ integer digits, representing the capacity level installed at the centers at each time period. Therefore, a given solution generated during the search, Z, is defined by

$$Z = \begin{pmatrix} Z^1 \\ \dots \\ Z^{|\boldsymbol{T}|} \end{pmatrix} = \begin{pmatrix} Z_1^1 & \dots & Z_{|\boldsymbol{N}|}^1 \\ \vdots & \ddots & \vdots \\ Z_1^{|\boldsymbol{T}|} & \dots & Z_{|\boldsymbol{N}|}^{|\boldsymbol{T}|} \end{pmatrix},$$

where Z^1 and $Z^{|\boldsymbol{T}|}$ denote the airport capacities for the first and last time periods, respectively. The outline of the algorithm is shown in Figure 42.

The airport capacity expansion procedure can be implemented considering various types of algorithms. In this application, we used the Simulated Annealing algorithm (SAA) as it was proven to provide good solutions for other dynamic capacity expansion problems

(Antunes and Peeters 2001). The SAA starts with an initial feasible solution, and, in consecutive iterations, moves toward successive neighboring solutions of the current solution until some stopping criteria is met. The SAA uses a criterion to determine how current solutions are defined along the solution search. The choice criterion most commonly used is the Metropolis criterion, built upon the Bolzmann-Gibbs distribution. According to the Metropolis criterion, a neighbor solution, Z^K, of the current solution, Z^C, is defined as the new current solution with a probability given by

$$p = \min\left\{1, \exp\left(-\frac{\Delta fitness}{\theta}\right)\right\},$$

where *Δfitness* stands for the difference of values between the current and neighbor solutions [$fitness(Z^K) - fitness(Z^C)$], and θ denotes the temperature of the system, a parameter whose value decreases during the annealing process. According to the Metropolis criterion, neighbor solutions with higher value (this is a maximization problem) are always selected as new current solution (p=1), while solutions with lower value may be selected, but with larger probability at the beginning of the annealing process (as θ decreases).

The way the temperature of the system, θ, decreases along the annealing process is defined by the cooling schedule. It was assumed in this study that the cooling schedule is defined following the principles adopted by Johnson et al. (1989) in their annealing algorithm for the graph partitioning problem. Those authors defined a schedule involving four parameters: initial temperature (θ_1), temperature length (δ), cooling rate (ρ), and stopping number (η). The initial temperature defines the rate at which neighbor solutions with value x% lower than the value of the current solution are retained in the beginning of the annealing process. The temperature length is the minimum number of candidate solutions to be tried at each temperature. If the algorithm is unable to find at least one better single solution or a better average solution, the temperature is decreased. The cooling rate is the rate at which temperature is decreased. The stopping number is the maximum number of temperature reductions that may occur without finding any solution improvements. When this number is reached the system becomes "frozen", and the annealing process reaches the end.

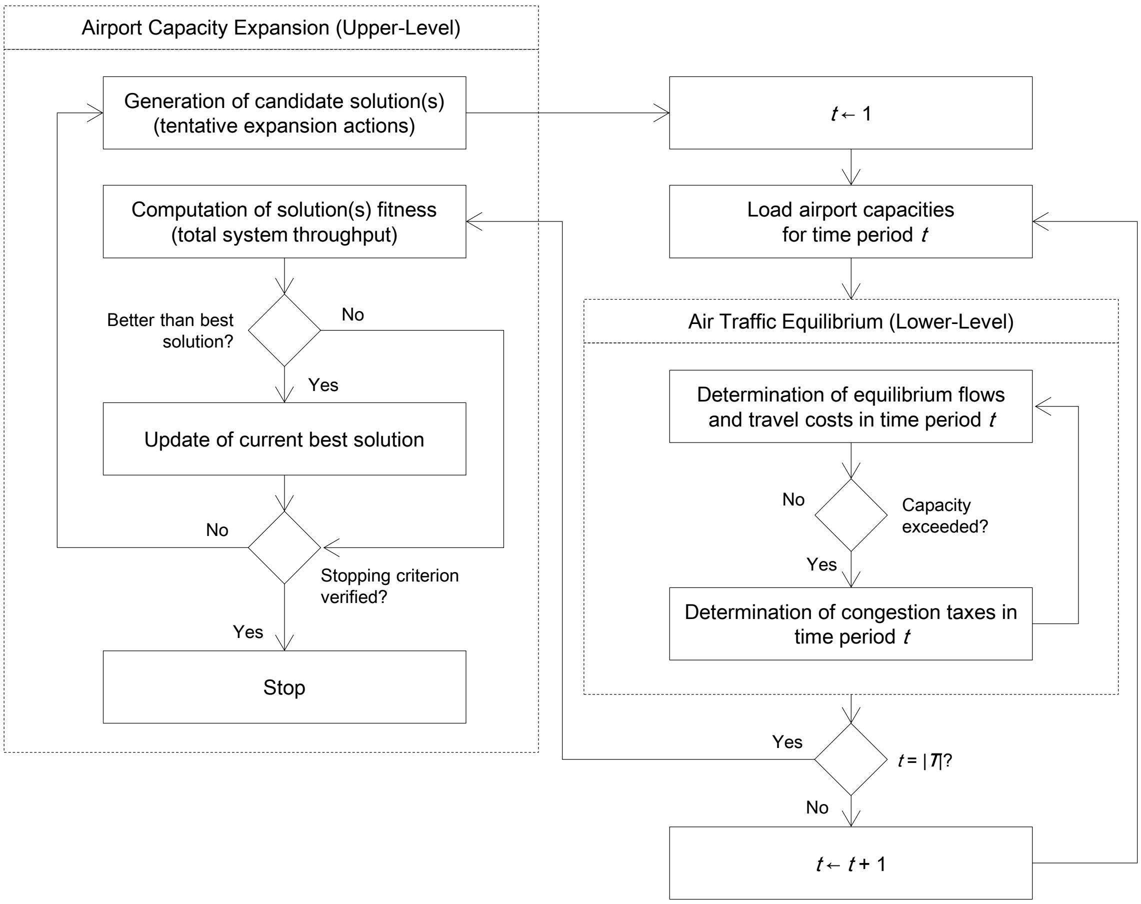

Figure 42 – Outline of the solution approach developed for solving the dynamic and deterministic model

The generation of neighboring solutions is accomplished, in our implementation, through the following procedure. First, a center j and a time period t of the current solution, Z^C, are chosen at random, with all centers and time periods having the same probability of being chosen. Then, the capacity installed in the center at the chosen time period goes through a transformation selected at random. This transformation may either consist of increasing the installed capacity by one level (Add), decreasing the installed capacity by one level (Drop), or swapping one capacity level with another center also selected at random (Interchange).

Each candidate solution generated during the search is followed by a procedure to detect and correct any possible infeasibility regarding Constraints (5) of the model, which states, as already mentioned, that the installed capacity in each center cannot be decreased from a time period to the next. The correction is made towards the front, starting from the initial period. For example, consider a 3-period problem in which the (installed) capacity of a given center corresponds to capacity layout 1, out of a maximum of two capacity layouts that can be applied. If the center is not expanded in any of the time periods, Z = [$z_{layout1}$, $z_{layout1}$, $z_{layout1}$]. If the capacity sequence for the center (for a given candidate solution) is [$z_{layout1}$, $z_{layout1}$, $z_{layout2}$], and the selected transformation consists of increasing the capacity by one level in the first time period (through Add), the sequence would be [$z_{layout2}$, $z_{layout1}$, $z_{layout2}$]. To avoid the decrease of capacity from the first time period to the second, the candidate capacity would be adjusted to [$z_{layout2}$, $z_{layout2}$, $z_{layout2}$]. The possible neighborhood solutions that can be generated from the initial solution, and corresponding capacity adjustments that may be applied to correct infeasibilities, are shown in Figure 43. For each solution generated during the search (feasible with regard to Constraints 5), a local search procedure is performed until the solution value does not improve or does no longer satisfy the budget constraints. For this purpose, a simple Add procedure was considered (as described above). The pseudo-code of the SAA is depicted in Figure 44.

2.3 Application example

The type of results that can be obtained through the application of the dynamic and deterministic airport network capacity expansion model will be illustrated for Instance #1 of a set of random instances generated for a region with six population centers, each one served by one airport. The application consists in analyzing the implications for the airport network in two time periods, as a result of 25 and 75 percent increases of the size of all population centers and in determining the expansion actions to implement in each time period in response to the population increase. A total budget of 40×10^8\$ equally distributed across the two time periods was considered for expanding the airport network.

Below we provide detailed information on the data used to run the model and on the results obtained through its application.

2.3.1 Data

The population centers are randomly distributed over a square-shaped region with 4,000 × 4,000 km^2 (Table 58). The sizes of the population centers were randomly determined to follow Zipf's rank-size rule considering the maximum population of 20 million for the largest center.

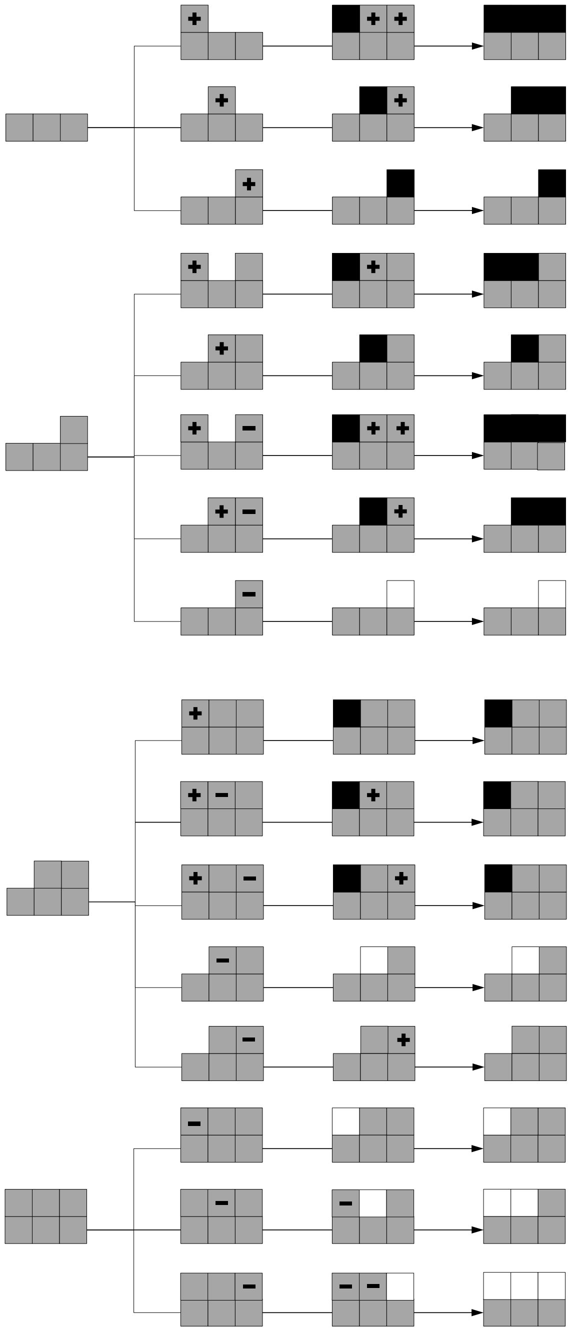

Figure 43 – Capacity adjustments considering 2 capacity levels in 3-period problems

```
INITIALIZATION:
1)  Set initial airports capacity, S, as current solution, Z^C:
        1.1) Z^C ← S
        1.2) fitness(Z^C) ← evaluate Z^C
2)  Set current solution, Z^C, as best solution, Z^B:
        2.1) Z^B ← Z^C
        2.2) fitness(Z^B) ← evaluate Z^B
GENERATION OF CANDIDATE SOLUTIONS:
3)  it ← 1; n ← 0
4)  Set cooling parameters (θ1, δ, ρ, and η)
5)  θ ← θ1
6)  Generate and evaluate solution in the neighborhood of Z^C, Z^K:
        6.1) Select center and time period at random in Z^C
        6.2) Perform Add, Drop or Interchange with equal probability
        6.3) Repair infeasibilities in Z^K
        6.4) fitness(Z^K) ← evaluate Z^K
7)  Local search and update of Z^B:
        7.1) Perform Add from Z^K and define solution found as Z^K*
        7.2) if fitness(Z^K*)>fitness(Z^B) then
                 Z^B ← Z^K*
                 fitness(Z^B) ← fitness(Z^K*)
             end-if
8)  Update current solution:
        8.1) Choose at random p in [0, 1]
        8.2) Δfitness ← fitness(Z^C)-fitness(Z^K)
        8.3) if p ≤ min{1; exp(-Δfitness/θ)} then
                 Z^C ← Z^K
                 fitness(Z^C) ← fitness(Z^K)
             end-if
9)  Decrease temperature or not:
        if best solution or average solution (Z^B) improved then
             it ← 1
        else
             it ← it+1
             move to 5
        end-if
        if it=δ then
             θ ← θ.ρ
             n ← n+1
        end-if
STOPPING CRITERIA:
9) Stopping criteria:
    if n < η then
       move to 6
    else
       STOP.
    end-if
```

Figure 44 – Pseudo-code of the panoramic approach developed to solve the dynamic and deterministic model

All centers are served by an airport. Airports can have six possible layouts. The possible layouts and corresponding airport capacities are listed in Table 59.

Table 58 – Coordinates and population of centers

Center	Coordinates (km)		Population
	X	Y	(10^6 inhabitants)
1	369	3026	17.162
2	3722	1535	7.180
3	2685	1534	4.474
4	3539	2078	3.295
5	952	1051	2.658
6	3014	3637	1.948

Table 59 – Possible airport layouts and corresponding increase in capacity (x10^3 pax/day)

Layout	Runway configuration	Capacity (10^3 pax/day)
1	Single runway	40
2	Two close parallel runways	60
3	Two medium spaced parallel runways	70
4	Two independent parallel runways	80
5	Three runways (two close runways plus one)	100
6	Four runways (two pairs of close parallel runways)	120

The demand function, the modal split factor, the route choice (logit) model, and the cost functions (C_1 and C_2) are as follows:

$$q_{jk}^t = 1.8 p_j^t p_k^t \phi_{jk}^t {c_{jk}^t}^{-0.5}, \quad \forall j,k \in \boldsymbol{N}, \quad \forall t \in \boldsymbol{T} \tag{14}$$

$$v_{jkr}^t = \frac{e^{-0.03 c_{jkr}^t}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-0.03 c_{jkp}^t}} q_{jk}^t, \quad \forall j,k \in \boldsymbol{N}, \quad \forall r \in \boldsymbol{R}_{jk}, \quad \forall t \in \boldsymbol{T} \tag{15}$$

$$\phi_{jk}^{t} = \begin{cases} 0 \Leftarrow l_{jk} \le l_{jk\min} \\ \dfrac{l_{jk} - l_{jk\min}}{l_{jk\max} - l_{jk\min}} \Leftarrow \le l_{jk\min} < l_{jk} < l_{jk\max} \\ 1 \Leftarrow l_{jk} \ge l_{jk\max} \end{cases}, \ \forall j,k \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \tag{16}$$

where l_{jk} is the (Euclidean) distance between centers j and k, $l_{jk_{\min}}$ = 200 km (distance below which all traffic is by land) and $l_{jk_{\max}}$ = 1000 km (distance above which all traffic is by air).

$$C_1\left(d_l, u_l^t\right) = \begin{cases} \left(1 - \dfrac{0.5}{20} \times u_l^t\right) \times 0.06 \times d_l \Leftarrow u_l^t < 20 \\ 0.03 \times d_l \Leftarrow u_l^t \ge 20 \end{cases}, \ \forall l \in \boldsymbol{L}, \ \forall t \in \boldsymbol{T} \tag{17}$$

$$C_2\left(w_n^t / z_n^t\right) = \begin{cases} 20 \Leftarrow w_n^t / z_n^t \le 0.8 \\ 100 \times w_n^t / z_n^t - 60 \Leftarrow w_n^t / z_n^t > 0.8 \end{cases}, \ \forall n \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \tag{18}$$

The units for the variables included in these expressions are: q^t_{jk}, v^t_{jkr}, u^t_l, w^t_n, and z^t_n, 10^3 pax/day; p^t_j, million inhabitants; c, C_1, and C_2, \$/pax; and l_{jk} and d_l, km.

The existing airport network is described in Figure 45 and Table 60. All airports are single runway airports (Layout 1). The airports of the two largest centers (Centers 1 and 2) are hub airports, and other airports are non-hub airports, serving only as trip origins or destinations. The two hub airports are somewhat congested (the utilization rate exceeds 80% in both cases), but have enough capacity to serve all demand as the congestion taxes equal zero. The total system throughput is 100.9×10^3 pax/day.

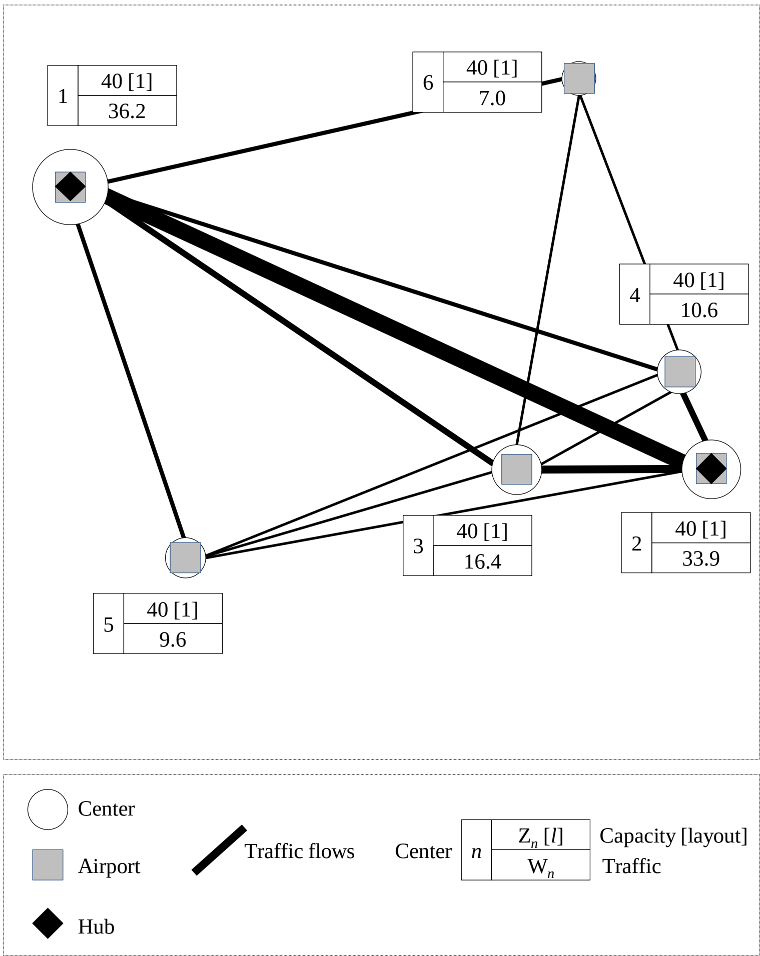

Figure 45 – Existing airport network

Table 60 – Airport information for the existing airport network

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	40	36.2	91	30.6	0.0
2	40	33.9	85	24.8	0.0
3	40	16.4	41	20.0	0.0
4	40	10.6	26	20.0	0.0
5	40	9.6	24	20.0	0.0
6	40	7.0	17	20.0	0.0

The expenditure involved in the expansion of airports is presented in Table 61.

Table 61 – Airport expansion costs (x10^8\$)

Cost (10^8 \$)						
Initial airport layout	Final airport layout 1	2	3	4	5	6
No airport	8	10	12	14	16	18
1	-	6	8	9	12	14
2	-	-	5	6	9	11
3	-	-	-	4	7	9
4	-	-	-	-	6	8
5	-	-	-	-	-	5

2.3.2 Results

As stated before, the application consists in determining the expansion actions to implement in the airport network in response to a 25% increase of the size of all population centers in a first time period, followed by an increase of 50% in a second time period (total increase of 75%), as a function of the budget available for the improvement of the existing airport network.

The solutions shown below were obtained by the SAA, presented in Subsection 2.2. The SAA uses parameters to guide the search – θ_1, δ, ρ, and η –, which may be estimated through trial-and-error. Alternatively, we have used in our study the values recommended in Antunes and Peeters (2001). These values are: θ_1=0.13×$fitness_0$ ($fitness_0$ denotes the value of the “do-nothing” solution); δ =3|$\boldsymbol{N}$||$\boldsymbol{T}$| (|$\boldsymbol{N}$| is the number of centers, and |$\boldsymbol{T}$| is the number of time periods); ρ =0.3; and η=6. In addition, since the SAA is an algorithm which uses randomization within the solution search, it was run with five different random seeds and the solution shown is the best one obtained.

According to the outcomes of the model for the first time period, the airport in Center 1 would be upgraded to Layout 5 (“two close runways plus one”), and the airport in

Center 2 would be upgraded to Layout 3 (“two medium spaced parallel runways”) (Figure 46 and Table 62). Their capacity would therefore increase from 40×10^3 to 100×10^3 and 70×10^3 pax/day, respectively. Since the expenditure involved in updating a single runway airport to an airport with three runways and to an airport with two medium spaced parallel runways are 12×10^8\$ and 8×10^8\$, respectively, the total expenditure would be 20×10^8\$ (equal to the budget available in the first time period). With these improvements to the airport network, total throughput would be 166.5×10^3 pax/day, and only the airport in Center 2 would present some congestion problems (the utilization rate exceeds 80%). As for the second time period, the airport in Center 1 would be upgraded to Layout 6 (“two pairs of close parallel runways”), the airport in Center 2 would be upgraded to Layout 5 (“two close runways plus one”), and the airport in Center 3 would be upgraded to Layout 3 (“two medium spaced parallel runways”) (Figure 47 and Table 63). The total expenditure would be 20×10^8\$ (5×10^8\$ + 7×10^8\$ + 8×10^8\$), which equals the budget available in the second time period. The budget available would not be enough to eliminate the congestion problems at the airports in Centers 2 and 4, but their capacity would be enough to serve all demand (the airport in Center 1 would also present congestion problems but it could not be further improved). The total throughput in the second time period would be 315.4×10^3 pax/day, and the total throughput over the two time periods would be 481.9×10^3 pax/day.

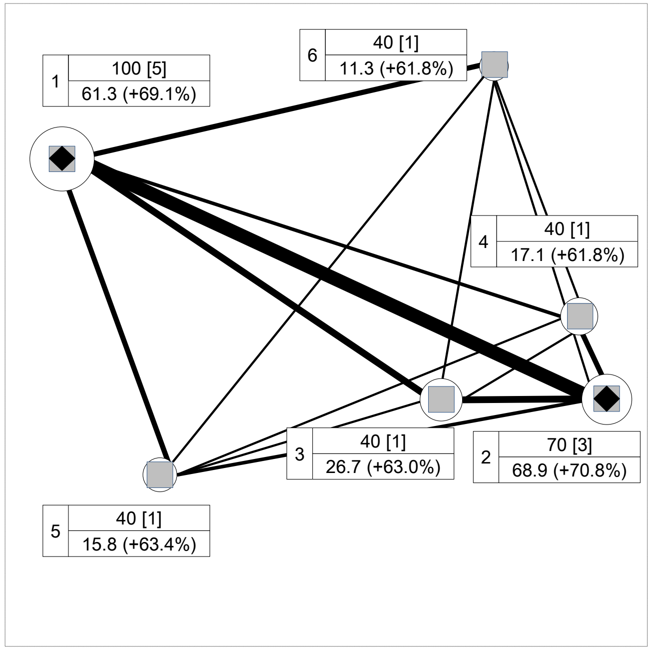

Figure 46 – Optimum airport network in *t*=1

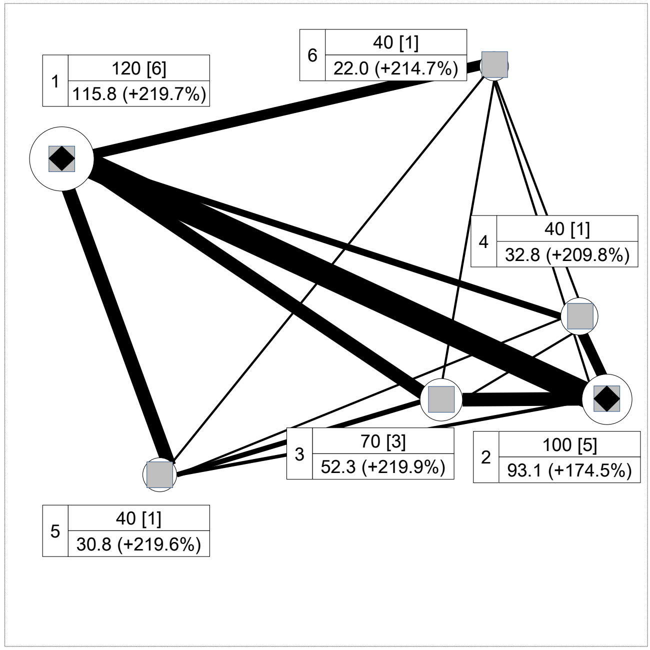

Figure 47 – Optimum airport network in *t*=2

Table 62 – Airport information for the optimum airport network in *t*=1

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	100	61.3	61	20.0	0.0
2	70	57.3	82	21.8	0.0
3	40	26.7	67	20.0	0.0
4	40	17.1	43	20.0	0.0
5	40	15.8	39	20.0	0.0
6	40	11.3	28	20.0	0.0

Table 63 – Airport information for the optimum airport network in *t*=2

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	115.8	97	36.5	0.0
2	100	93.1	93	33.1	0.0
3	70	52.3	75	20.0	0.0
4	40	32.8	82	21.9	0.0
5	40	30.8	77	20.0	0.0
6	40	22.0	55	20.0	0.0

The solution approach developed for solving the model can be designated as panoramic, as it takes into account the effect that planning decisions have on the capacity needs over future time periods. A possible alternative for solving the dynamic model would be to solve a static model (as the one presented in Chapter 2) for each time period, given the “optimum” solutions identified for the previous time periods. This solution approach is designated as myopic.

A myopic approach was also used to solve the dynamic and deterministic model for the test instance presented before. The generation of the expansion actions to apply to the airport network was accomplished through the Add+Interchange algorithm (AIA). The AIA starts with the solution found for the previous time period (for the first time period, it starts from the initial airport network) and, in successive iterations, selects the one-level airport upgrade change that allows the best improvement of the objective function, until no further improvement is feasible (within the budget available). Then, starting with the solution found, it selects the combination of feasible one-level capacity swaps that allow the best improvement of the objective function. The two procedures are repeated sequentially while solutions keep improving. For an extended explanation of the algorithm, the reader is referred to Chapter 3.

According to the results obtained through the myopic approach, the airports in Centers 1 and 2 would be upgraded to Layout 4 (“two independent parallel runways”), and their capacity would therefore increase from 40 to 80×10^3 pax/day (Figure 48 and Table 64). These changes to the airport network would be less costly than the ones obtained with the panoramic approach (18×10^8\$ vs. 20×10^8\$) and would lead to a larger system throughput (167.0×10^3 vs. 166.5×10^3 pax/day, which corresponds to an increase of 0.3%). As for the second time period, the airports in Centers 1 and 2 would also be upgraded to Layouts 6 and 5, respectively, but the airport in Center 3 would only be upgraded to Layout 2 ("two close parallel runways") (Figure 49 and Table 65). The total expenditure would also be 20×10^8\$ (8×10^8\$ + 6×10^8\$ + 6×10^8\$), but would lead to a smaller system throughput (313.3×10^3 vs. 315.4×10^3 pax/day, which corresponds to a decrease of 0.7%). The total throughput over the two time periods would be 480.3×10^3 pax/day, which is 0.3% worse than the panoramic solution.

3. Stochastic and static model

The dynamic model described in the previous section attempts to determine the capacity needs of an airport network over a specified time horizon in an optimal or near-optimal manner. While capturing more of the complexity inherent in real-world problems than static and deterministic formulations, the model assumes that input parameters are constant or vary deterministically over time. In this section, we will address the stochastic nature of real-world problems. Stochastic planning, and in particular, stochastic formulations, take into account the randomness of the model parameters.

Rosenhead et al. (1972) classifies decision-making environments into certainty, risk and uncertainty, where risk applies when the randomness of parameters is governed by a known probability distribution (stochastic planning), and uncertainty situation when there are no information about probabilities (robust planning). This study deals with the former.

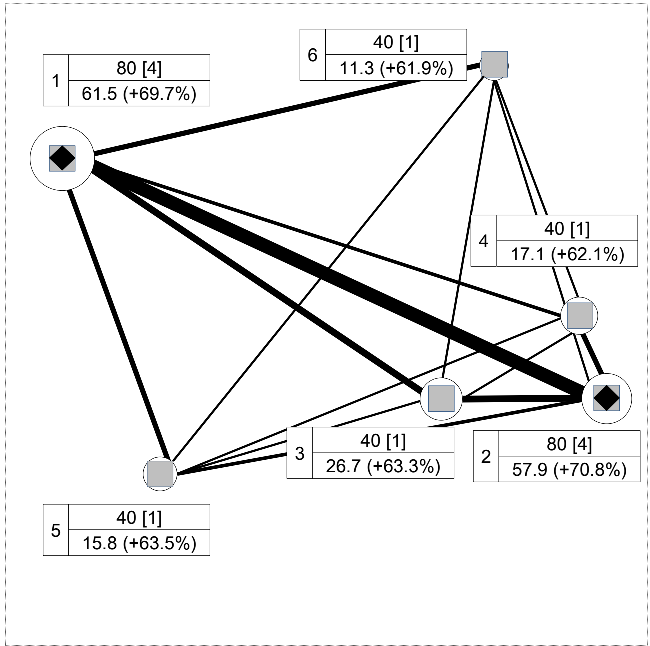

Figure 48 – Optimum airport network in *t*=1 with myopic approach

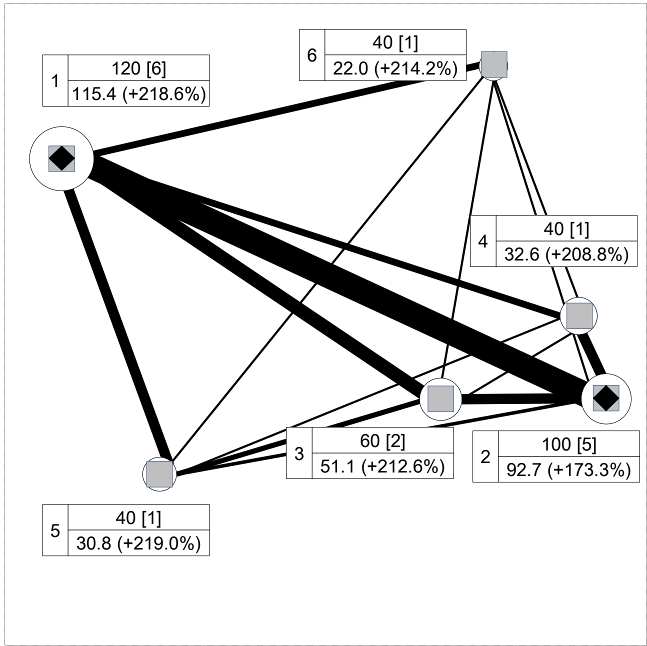

Figure 49 – Optimum airport network in *t*=2 with myopic approach

Table 64 – Airport information for the optimum airport network in *t*=1 with myopic approach

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	80	61.5	77	20.0	77.0
2	80	57.9	72	20.0	72.0
3	40	26.7	67	20.0	67.0
4	40	17.1	43	20.0	43.0
5	40	15.8	39	20.0	39.0
6	40	11.3	28	20.0	28.0

Table 65 – Airport information for the optimum airport network in *t*=2 with myopic approach

Center	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	115.4	96	36.2	0.0
2	100	92.7	93	32.7	0.0
3	60	51.1	85	25.2	0.0
4	40	32.6	82	21.6	0.0
5	40	30.8	77	20.0	0.0
6	40	22.0	55	20.0	0.0

Owen and Daskin (1998) brakes down stochastic problems into two categories: probabilistic planning and scenario planning (other authors, such as Mulvey et al. 1995, distinguish scenario planning and stochastic programming). Probabilistic models consider explicitly probability distributions for the parameters, and seek solutions by maximizing the probability that the performance of the system is good, or constraining the probability that it is bad, under suitable definitions of "good" and "bad" (Snyder 2005). Scenario planning models consider a set of possible parameter values with a given probability of occurrence, and the objective is to find solutions which perform well under all scenarios.

A common approach in scenario planning is to optimize the average case or the worst case performance over all scenarios. However, such approaches may result in underused or overused facilities for most of the time. Other approaches are due to Sheppard (1974), who developed a model which seeks to minimize the expected cost over all scenarios, Schilling (1982), in which the initial location for the facilities are those that are common across the optimal locations for most scenarios, and Daskin et al. (1992), who propose a forecast horizon-based approach. Other scenario planning approaches use the concept of regret, being regret defined for each scenario and given by the sum of the differences between the value of the solution adopted (called compromise solution) and the value of the optimal solution for each scenario. Ghosh and McLafferty (1982) proposed a model which minimizes the sum of the regrets (or the sum of the squared regrets) over all scenarios, and Daskin et al. (1997) proposed a model called the α-reliable p-median minimax regret model, which seeks solutions that minimize the maximum regret with respect to a set of scenarios. Another commonly used criterion is the minimization of the expected regret, given by the sum of the weighted regrets for all scenarios with their probability or weight (Owen and Daskin 1998). The stochastic airport network capacity expansion model presented in this section is based on the formulation of the latter.

The following subsections discuss a formulation for the stochastic and static airport network capacity expansion model and describe a heuristic solution method used to solve it. The type of results that can be expected from the application of the model is then illustrated for the same test instance used previously.

3.1 Model formulation

Let $\boldsymbol{I}$ denote the set of scenarios under consideration. For a given scenario i in $\boldsymbol{I}$, consider the following definitions:

$T_i\ (Z)$ - total system throughput for scenario i for the compromise capacities, Z (that is, for a solution for the stochastic model).

$T^*_i\ (Z^*_i)$ - total system throughput for scenario i for the scenario-driven capacities, Z^*_i, which are obtained by solving the deterministic model (presented in Chapter 2) for the conditions of each scenario ($Z^*_i=\{z^*_{1i}, \ldots, z^*_{|N|i}\}$, where z^*_{ji} denotes the “optimum” capacity of airport j for the conditions of scenario i). This represents the maximum total system throughput attained to the conditions of each scenario.

In addition to the above definitions, consider the following notation:

p_{ji} - population of center *j* for scenario *i*

h_i - occurrence probability (or weight) of scenario *i*

q_{jki} - O-D traffic flow between centers *j* and *k* for scenario *i*

w_{ji} - traffic flow in center *j* for scenario *i*

u_{li} - traffic flow on leg *l* for scenario *i*

v_{jkri} - traffic flow in route *r* connecting centers *j* and *k* for scenario *i*

c_{jk} - average travel cost between centers *j* and *k* for scenario *i*

c_{jkri} - travel cost for route *r* connecting centers *j* and *k* for scenario *i*

x_{ji} - congestion tax to apply in center *j* for scenario *i*

The remaining notation is the same presented before for the dynamic model, except for index *t*. The mathematical formulation of the stochastic and static model is as follows:

$$\min \sum_{i \in \boldsymbol{I}} h_i \, R_i \tag{18}$$

subject to:

$$R_i - \left[T_i(Z) - T_i^*\left(Z_i^*\right)\right] = 0, \quad \forall i \in \boldsymbol{I}. \tag{19}$$

$$z_j \geq w_{ji}, \quad \forall j \in \boldsymbol{N}, \quad \forall i \in \boldsymbol{I} \tag{20}$$

$$z_j = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm} \, y_{jm}, \quad \forall j \in \boldsymbol{N} \tag{21}$$

$$\sum_{m \in \boldsymbol{M}_j} y_{jm} \leq 1, \ \forall j \in \boldsymbol{N} \tag{22}$$

$$\sum_{j \in \boldsymbol{N}} \sum_{m \in \boldsymbol{M}_j} y_{jm} e_{jm} \leq b \tag{23}$$

$$q_{jki} = Q\left(p_{ji}, p_{ki}, \phi_{jk}, c_{jki}\right), \ \forall j,k \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I} \tag{24}$$

$$v_{jkri} = \frac{e^{-\gamma c_{jkri}}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkpi}}} q_{jki}, \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk}, \ \forall i \in \boldsymbol{I} \tag{25}$$

$$u_{li} = \sum_{j \in \mathbf{N}} \sum_{k \in \mathbf{N}} \sum_{r \in \mathbf{R}_l} v_{jkri}, \ \forall l \in \mathbf{L}, \ \forall i \in \mathbf{I} \tag{26}$$

$$w_{ji} = \sum_{l \in \mathbf{L}_j} u_{li}, \ \forall j \in \mathbf{N}, \ \forall i \in \mathbf{I} \tag{27}$$

$$c_{jkri} = \sum_{l \in \mathbf{L}_{jkr}} C_1\left(d_l, u_{li}\right) + \sum_{n \in \mathbf{N}_{jkr}} \left[C_2\left(\frac{w_{ni}}{z_n}\right) + x_{ni}\right], \ \forall j,k \in \mathbf{N}, \ \forall r \in \mathbf{R}_{jk}, \ \forall i \in \mathbf{I} \tag{28}$$

$$c_{jki} = \frac{\sum_{r \in \boldsymbol{R}_{jk}} c_{jkri} v_{jkri}}{q_{jki}}, \ \forall j,k \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I} \tag{29}$$

$$y_{jm} \in \{0,1\}, \ \forall j \in \mathbf{N}, \ \forall m \in \mathbf{M}_j \tag{30}$$

The objective function (18) of the model expresses the minimization of expected regret, which is defined by the sum of the regrets for the scenarios under consideration, affected by their weight.

Constraints (19) calculate the regret associated to each scenario. The regret associated to each scenario is given by the difference of total system throughput for the scenario-driven capacities and for the compromise capacities. Note that the compromise capacities are common among all scenarios and must be determined before knowing which scenario is realized. The equilibrium pattern within the airport network, however, is scenario specific, and the variables related with traffic and travel costs are defined for each scenario. Therefore, the total system throughput at scenario *i* for the compromise capacities and for the scenario-driven capacities can be written in the following way:

$$T_i(Z) = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki} \text{ , and}$$

$$T_i^*(Z_i^*) = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki}^* \text{ ,}$$

where q^*_{jki} denotes the O-D traffic flows for scenario *I* for the scenario-driven capacities. Constraints (19) can, therefore, be rewritten as follows:

$$R_i - \left(\sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki} - \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki}^* \right) = 0, \ \ \forall i \in \boldsymbol{I}.$$

Constraints (20) establish that the (compromise) capacity of the centers must be able to accommodate the traffic flow for all scenarios.

Constraints (21) state that the capacities of the centers are given by the sum of their initial capacities and the capacity increase due to the expansion action applied.

Constraints (22) ensure that at most one expansion action will be applied for each center.

Constraints (23) guarantee that the total expenditure will comply with the budget available for expansion actions.

Constraints (24) are the O-D demand functions relating the traffic flows between each pair of centers with their size, with a modal split factor, and with the average travel cost between the centers. The size of the centers and travel cost are scenario specific.

Constraints (25) assign the O-D traffic flows to flight routes as a function of the average travel cost through a logit model.

Constrains (26) calculate the traffic flow in each flight leg by summing the traffic flows in the routes containing those legs.

Constrains (27) compute the enplanements at the centers (airports) in each time period by summing the traffic flows in the legs with start point in those centers.

Constraints (28) compute the travel cost for each route.

Constraints (29) calculate the average (generalized) travel cost for each pair of centers.

Finally, constraints (30) define the capacity expansion variables as binary.

3.2 Solution approach

The algorithm developed to solve the stochastic model is very similar to the one proposed in Chapter 3 to solve the deterministic model. The difference is that for each candidate solution generated (encoding a tentative set of compromise capacities), the equilibrium is computed for the conditions of each scenario. Each scenario-driven equilibrium for the compromise capacities is associated to a total system throughput

($T_i(Z)$ for each scenario i in $\boldsymbol{I}$). The assessment of the candidate solutions is made with regard to constraints (19) using the value of the scenario-driven solutions (T^*_i (Z^*_i) for each scenario i in $\boldsymbol{I}$), which are computed *a priori*. The value (expected regret) of each candidate solution Z generated is denoted by *fitness*($Z|Z^*$). The outline of the algorithm is shown in Figure 50. The generation of the candidate solutions was made using the Add+Interchange algorithm (depicted in Figure 51).

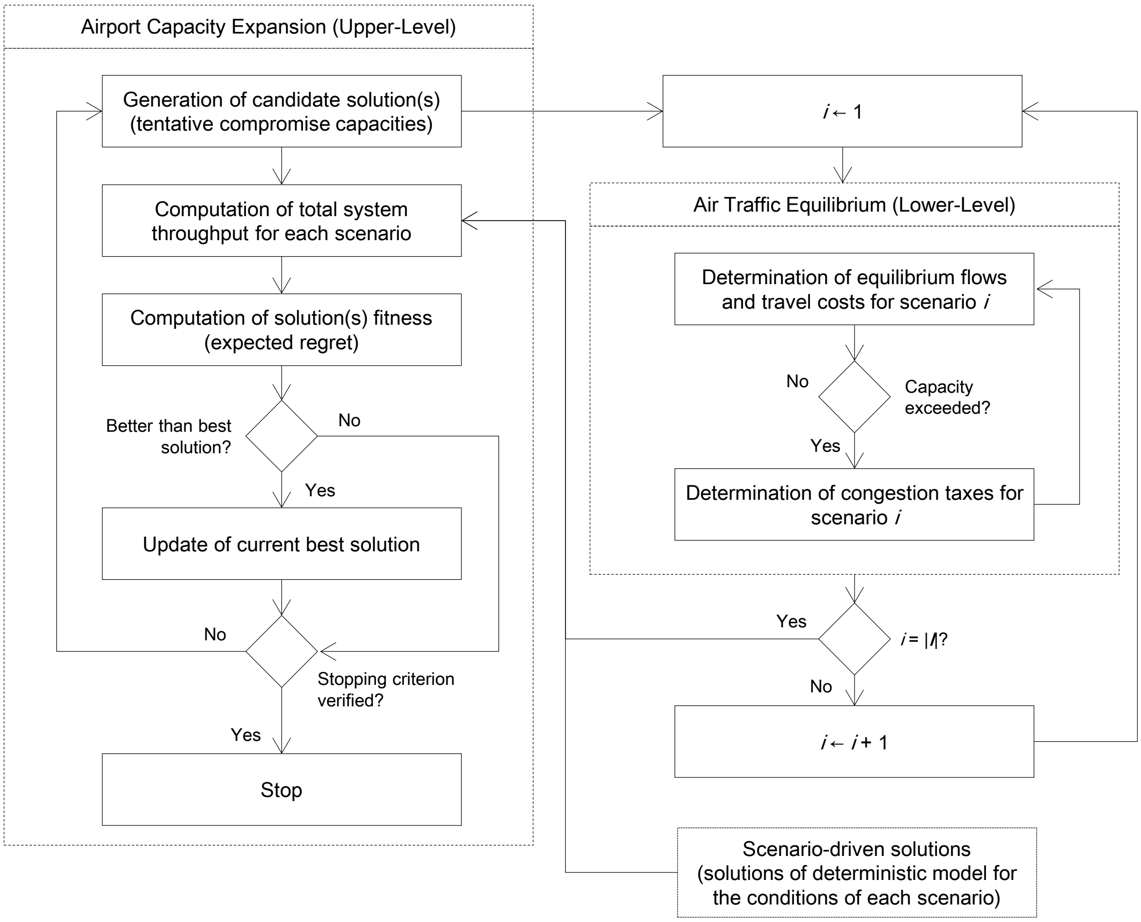

Figure 50 – Outline of the algorithm developed to solve the stochastic and static model

```
INITIALIZATION:
1)  Set initial airports capacity, S, as current solution, Z^C:
        1.1) Z^C ← S
        1.2) fitness(Z^C|Z*) ← fitness(S|Z*)
2)  Set current solution, Z^C, as best solution, Z^B:
        2.1) Z^B ← Z^C
        2.2) fitness(Z^B|Z*) ← fitness(Z^C|Z*)
GENERATION OF CANDIDATE SOLUTIONS:
3)  Add:
        3.1) Upgrade the capacity of each airport in Z^C one-level
        3.2) Denote Z^N as the neighbor solution with the airport upgrade
             change that has the best fitness
        3.3) Move or not:
                  if fitness(Z^N|Z*) > fitness(Z^C|Z*) then
                       Z^C ← Z^N
                       fitness(Z^C|Z*) ← fitness(Z^N|Z*)
                       move to 3)
                  else
                       move to 4)
                  end-if
4)  Interchange:
        4.1) Combine one-level upgrade and downgrade changes for each
             pair of airports in Z^C
        4.2) Denote Z^N as the neighbor solution with the airport upgrade
             and downgrade changes that has the best fitness
        4.3) Move or not:
                  if fitness(Z^N|Z*) > fitness(Z^C|Z*) then
                       Z^C ← Z^N
                       fitness(Z^C|Z*) ← fitness(Z^N|Z*)
                       move to 4)
                  else
                       move to 5)
                  end-if
STOPPING CRITERIA:
5)  Update best solution or stop search:
        if fitness(Z^C|Z*) > fitness(Z^B|Z*) then
             move to 2)
        else
             STOP.
        end-if
```

Figure 51 – Pseudo-code of the Add+Interchange algorithm developed to solve the stochastic and static model

3.3 Application example

The stochastic and static model was applied to the same 6-airport test instance used to exemplify the results obtained by the dynamic and deterministic model in Section 2. An average (expected) increase of 75% for the population of the centers was considered (equal to the total population increase for the second time period considered in the application example developed for the dynamic model), to which a random deviation ranging from -25% to +25% was summed for 5 independent scenarios. The same probability was assumed for all scenarios – the increase of the population of the centers for the scenarios is depicted in Table 66. It is considered a budget of 40×10^8\$ for expanding the network (equal to the total budget available over the two time periods considered for the dynamic and deterministic model). Table 67 to Table 71 show the airport information for the scenario-driven capacities (left) and for the compromise capacities (right), and Table 72 shows the regret associated with each scenario.

Table 66 – Increase of the population of the centers for the scenarios

Scenario	δp for the centers (%)					
	1	2	3	4	5	6
1	1.95	1.64	1.59	1.91	1.58	1.70
2	1.55	1.68	1.67	1.60	1.75	1.97
3	1.92	1.75	1.74	1.76	1.94	1.64
4	1.95	1.88	1.69	1.55	1.88	1.64
5	1.91	1.87	1.91	1.61	1.59	1.93
Average	1.86	1.76	1.72	1.69	1.75	1.78

According to the outcomes of the model, the airports in Centers 1and 2 would be upgraded to Layout 6 (“two pairs of close parallel runways”), and the airport in Center 3 would be upgraded to Layout 3 (“two medium spaced parallel runways”). The airports in Center 4, 5 and 6 would remain as single runway airports (Layout 1). The scenario-driven capacities (deterministic solutions) for Scenarios 1 and 4 are the same as of the compromise capacities, and, thus, the total system throughput for the scenario-driven capacities equals the total throughput for the compromise capacities, and the associated regret is zero. For Scenarios 2 and 3, the total system throughput would be maximized if the airports in Centers 3 and 5, and the airports in Centers 3 and 4, respectively, were upgraded to Layout 2 (“two close parallel runways”). With these improvements of the network, total system throughput for Scenarios 2 and 3 would be 293.7×10^3 and 327.3×10^3 pax/day, respectively. For the compromise capacities, total throughput would be 293.6×10^3 and 325.9×10^3 pax/day, respectively, representing regrets of 0.1 (293.7×10^3 - 293.6×10^3) and 1.4 (327.3×10^3 - 325.9×10^3). The scenario-driven capacities for Scenario 5 are different than the compromise capacities, but the total system throughput would be the same, and hence the regret would be zero. The expected regret, given by the sum of the regrets for the five scenarios affected by their weight (0.2), is 0.307.

The difference between the solutions for the static and stochastic model and for the dynamic and deterministic model arises from the restriction, in the latter case, imposed to the schedule for implementing changes in the network. Despite a total budget of 40×10^8\$ is provided in both cases, it is not possible to implement the solution provided by the stochastic model if the improvements in the network are to be made in two time periods with budgets of 20×10^8\$.

4. Dynamic and stochastic model

In this section, we present the mathematical formulation for the dynamic and stochastic airport network capacity expansion problem, derived from the two models presented previously. Then, we describe the solution method used to solve it, and present the results obtained for the model for the same test instance used previously.

Table 67 – Airport information for Scenario #1 with b=\$40x10^8: (left) with scenario-driven capacities; (right) with compromise capacities

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	120.0	100	40.0	2.3
2	120	99.9	83	23.2	0.0
3	70	54.5	78	20.0	0.0
4	40	36.4	91	30.9	0.0
5	40	29.7	74	20.0	0.0
6	40	24.3	61	20.0	0.0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	120.0	100	40.0	2.3
2	120	99.9	83	23.2	0.0
3	70	54.5	78	20.0	0.0
4	40	36.4	91	30.9	0.0
5	40	29.7	74	20.0	0.0
6	40	24.3	61	20.0	0.0

Table 68 – Airport information for Scenario #2 with b=\$40x10^8: (left) with scenario-driven capacities; (right) with compromise capacities

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	107.0	89	29.1	0.0
2	120	97.3	81	21.0	0.0
3	60	47.1	78	20.0	0.0
4	40	28.2	71	20.0	0.0
5	60	32.4	54	20.0	0.0
6	40	19.4	49	20.0	0.0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	106.9	89	29.1	0.0
2	120	97.2	81	21.0	0.0
3	70	47.1	67	20.0	0.0
4	40	28.2	71	20.0	0.0
5	40	32.3	81	20.8	0.0
6	40	19.4	49	20.0	0.0

Table 69 – Airport information for Scenario #3 with b=\$40x10^8: (left) with scenario-driven capacities; (right) with compromise capacities

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	120.0	100	40.0	6.7
2	120	101.1	84	24.3	0.0
3	60	49.4	82	22.4	0.0
4	60	37.5	62	20.0	0.0
5	40	34.8	87	26.9	0.0
6	40	21.4	54	20.0	0.0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost (\$/pax)	Tax (\$/pax)
1	120	120.0	100	40.0	5.8
2	120	100.8	84	24.0	0.0
3	70	49.7	71	20.0	0.0
4	40	36.0	90	30.0	0.0
5	40	34.8	87	26.9	0.0
6	40	21.4	53	20.0	0.0

Table 70 – Airport information for Scenario #4 with *b*=$40x10⁸: (left) with scenario-driven capacities; (right) with compromise capacities

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	117.8	98	38.2	0.0
2	120	103.0	86	25.8	0.0
3	70	51.5	74	20.0	0.0
4	40	30.0	75	20.0	0.0
5	40	28.0	70	20.0	0.0
6	40	20.1	50	20.0	0.0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	117.8	98	38.2	0.0
2	120	103.0	86	25.8	0.0
3	70	51.5	74	20.0	0.0
4	40	30.0	75	20.0	0.0
5	40	28.0	70	20.0	0.0
6	40	20.1	50	20.0	0.0

Table 71 – Airport information for Scenario #5 with *b*=$40x10⁸: (left) with scenario-driven capacities; (right) with compromise capacities

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	106.7	89	28.9	0.0
2	120	102.9	86	25.8	0.0
3	60	47.9	80	20.0	0.0
4	40	31.7	79	20.0	0.0
5	40	26.4	66	20.0	0.0
6	40	22.6	56	20.0	0.0

Airport	Capacity (10^3 pax/day)	Traffic (10^3 pax/day)	Utilization rate (%)	Cost ($/pax)	Tax ($/pax)
1	120	106.7	89	28.9	0.0
2	120	102.9	86	25.8	0.0
3	70	47.9	68	20.0	0.0
4	40	31.7	79	20.0	0.0
5	40	26.4	66	20.0	0.0
6	40	22.6	56	20.0	0.0

Table 72 – Determination of expected regret

Model	*Z*						*T*(Z*)*	*T(Z)*	*R*	*h*	*R.h*
-	120	120	70	40	40	40	-	-	-	-	-
Scenario	*Z**										
1	120	120	70	40	40	40	325.9	325.9	0.0	0.2	0.0
2	120	120	60	40	60	40	293.7	293.6	0.1	0.2	0.0
3	120	120	60	60	40	40	327.3	325.9	1.4	0.2	0.3
4	120	120	70	40	40	40	316.6	316.6	0.0	0.2	0.0
5	120	120	60	40	40	40	303.0	303.0	0.0	0.2	0.0
									Expected regret		0.307

4.1 Model formulation

The mathematical notation used in the formulation of the dynamic and stochastic model is similar to the notation used for the dynamic and deterministic model and for the static and stochastic model.

p^t_{ji} - population of center *j* in time period *t* for scenario *i*

q^t_{jki} - O-D traffic flow between centers *j* and *k* in time period *t* for scenario *i*

w^t_{ji} - traffic flow in center *j* in time period *t* for scenario *i*

u^t_{li} - traffic flow on leg *l* in time period *t* for scenario *i*

v^t_{jkri} - traffic flow in route *r* connecting centers *j* and *k* in time period *t* for scenario *i*

c^t_{jki} - average travel cost between centers *j* and *k* in time period *t* for scenario *i*

c^t_{jkri} - travel cost for route *r* connecting centers *j* and *k* in time period *t* for scenario *i*

x^t_{ji} - congestion tax to apply in center *j* in time period *t*.

The mathematical formulation of the model is as follows.

$$\min \sum_{i \in I} h_i \, R_i \tag{31}$$

subject to:

$$R_i - \left[T_i(Z) - T_i^*\left(Z_i^*\right) \right] = 0, \quad \forall i \in \boldsymbol{I}. \tag{32}$$

$$z_j^t \geq w_{ji}^t, \ \forall j \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{33}$$

$$z_j^t = s_j + \sum_{m \in \boldsymbol{M}_j} g_{jm} \, y_{jm}^t, \ \forall j \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \tag{34}$$

$$\sum_{m \in \boldsymbol{M}_j} y_{jm}^t \leq 1, \ \forall j \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \tag{35}$$

$$\sum_{m \in \mathbf{M}_j} y_{jm}^t g_{jm} \geq \sum_{m \in \mathbf{M}_j} y_{jm}^{t-1} g_{jm}, \ \forall j \in \mathbf{N}, \ \forall t \in \mathbf{T} \mid t > 1 \tag{36}$$

$$\sum_{j \in \boldsymbol{N}} \sum_{m \in \boldsymbol{M}_j} y_{jm}^t e_{jm} \leq b^t, \ \forall t \in \boldsymbol{T} \tag{37}$$

$$q_{jki}^t = Q\left(p_{ji}^t, p_{ki}^t, \phi_{jk}^t, c_{jki}^t\right), \ \forall j,k \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{38}$$

$$v_{jkri}^t = \frac{e^{-\gamma c_{jkri}^t}}{\sum_{p \in \boldsymbol{R}_{jk}} e^{-\gamma c_{jkpi}^t}} \, q_{jki}^t, \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{39}$$

$$u_{li}^t = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{r \in \boldsymbol{R}_l} v_{jkri}^t, \ \forall l \in \boldsymbol{L}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{40}$$

$$w_{ji}^t = \sum_{l \in \boldsymbol{L}_j} u_{li}^t, \ \forall j \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{41}$$

$$c_{jkri}^t = \sum_{l \in \boldsymbol{L}_{jkr}} C_1\left(d_l, u_{li}^t\right) + \sum_{n \in \boldsymbol{N}_{jkr}} \left[C_2\left(\frac{w_{ni}^t}{z_n^t}\right) + x_{ni}^t \right], \ \forall j,k \in \boldsymbol{N}, \ \forall r \in \boldsymbol{R}_{jk}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{42}$$

$$c_{jki}^{t} = \frac{\sum_{r \in \boldsymbol{R}_{jk}} c_{jkri}^{t} v_{jkri}^{t}}{q_{jki}^{t}}, \ \forall j,k \in \boldsymbol{N}, \ \forall i \in \boldsymbol{I}, \ \forall t \in \boldsymbol{T} \tag{43}$$

$$y_{jm}^{t} \in \{0,1\}, \ \forall j \in \boldsymbol{N}, \ \forall m \in \boldsymbol{M}_j, \ \forall t \in \boldsymbol{T} \tag{44}$$

The objective function (31) of the model expresses the minimization of expected regret.

Constraints (32) state that the regret associated to each scenario is given by the difference of total system throughput for the scenario-driven capacities and for the compromise capacities. As for the dynamic and static model, the total system throughput at scenario *i* for the compromise capacities and for the scenario-driven capacities can be written in the following way:

$$T_i(Z) = \sum_{t \in \boldsymbol{T}} \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki}^{t} \text{ , and}$$

$$T_i^{*}(Z_i^{*}) = \sum_{t \in \boldsymbol{T}} \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q*_{jki}^{t} \text{ ,}$$

where q^{*t}_{jki} denotes the O-D traffic flows for scenario *i* for the scenario-driven capacities for time period *t*. Constraints (32) can, therefore, be rewritten as follows:

$$R_i - \left(\sum_{t \in \boldsymbol{T}} \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q_{jki}^{t} - \sum_{t \in \boldsymbol{T}} \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} q*_{jki}^{t} \right) = 0, \ \forall i \in \boldsymbol{I}.$$

Constraints (33) establish that the capacity of the centers must be able to accommodate the traffic flow in all time periods for all scenarios under consideration.

Constraints (34) state that the capacities of the centers in each time period are given by the sum of their initial capacities and the capacity increase due to a given expansion action applied in that time period.

Constraints (35) ensure that at most one expansion action can be applied for each center in each time period.

Constraint (36) state that the installed capacity in each center cannot be decreased from a time period to the following.

Constrain (37) ensures that the budget available for expansion actions in each time period is not exceeded.

Constraints (38) compute the O-D traffic flows between the centers in each time period for all scenarios.

Constraints (39) assign the O-D traffic flows in each time period and scenario to itineraries.

Constrains (40) calculate the traffic flows in the legs by summing the traffic flows in the itineraries containing those legs.

Constrains (41) calculate the traffic flows in the centers by summing the traffic flows in the legs with start point in those centers.

Constraints (42) compute the (generalized) travel cost for the itineraries in each time period and scenario.

Constraints (43) calculate the average (generalized) travel cost for each pair of centers.

Constraints (44) define the capacity expansion variables as binary.

4.2 Solution approach

The solution approach developed for solving the dynamic and stochastic model shares the characteristics of the solution approaches developed for solving the dynamic and deterministic model (described in subsection 2.2) and for solving the stochastic and static model (subsection 3.2). Candidate solutions are encoded in $|\boldsymbol{T}|$ strings of $|\boldsymbol{N}|$ integer digits, representing the capacity level installed at the centers at each time period. For each candidate solution generated, the equilibrium is computed for the conditions of each scenario and time period under consideration. The assessment of the candidate solutions is made with regard to constraints (32) using the value of the scenario-driven solutions, determined *a priori* by solving the dynamic and deterministic model for the conditions of each scenario. The outline of the algorithm is shown in Figure 52. The Simulated Annealing algorithm was also used for the generation of candidate solutions.

4.3 Application example

The dynamic and stochastic model was applied to the same test instance presented in Subsection 2.3. As for the application of the dynamic and deterministic model, two time periods are considered: in the first time period, the size of the population centers increase by a deterministic amount of 25%, and in the second time period, they increased by a further average (expected) increase of 50% plus a random deviation ranging from -25% to +25% for 5 independent scenarios (Table 66). A budget of

$20 \times 10^8$$ is considered for each time period (similarly to the application example presented for the dynamic and deterministic model).

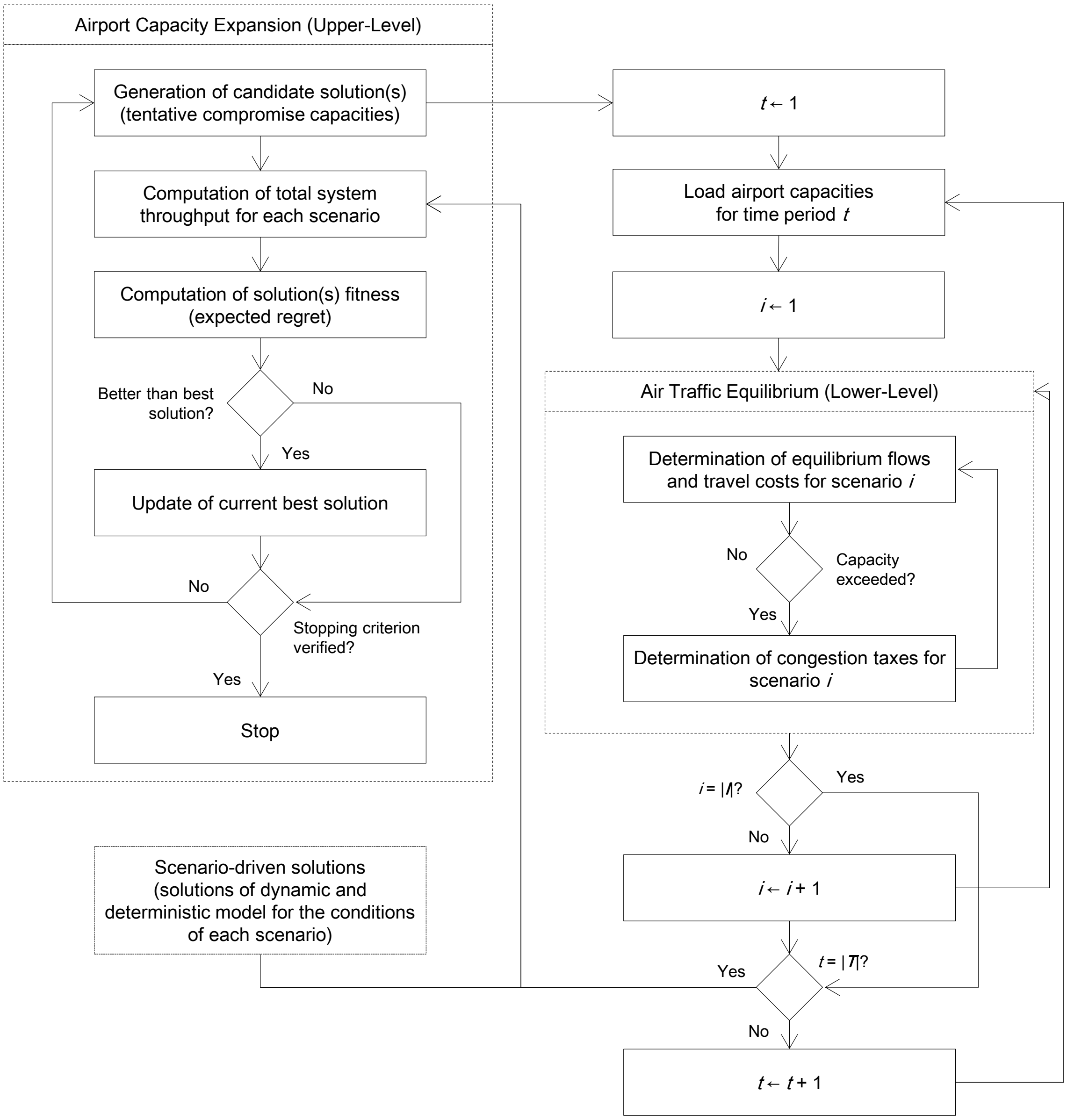

Figure 52 – Outline of the algorithm developed to solve the dynamic and stochastic model

According to the outcomes of the model (Table 73), the airports in Centers 1 and 2 would be upgraded to Layout 5 (“two close runways plus one”) and to Layout 3 (“two medium spaced parallel runways”), respectively, in the first time period, and would both be further improved in the second time period to Layout 6 (“two pairs of independent parallel runways”). The layout of the airport in Center 3 would also be upgraded in the second time period to Layout 2 (“two close parallel runways”). The scenario-driven capacities (solutions for the dynamic and deterministic model) for all scenarios are the same as of the compromise capacities, and, thus, the total system throughput for the scenario-driven capacities equals the total throughput for the compromise capacities, and the associated regret is zero.

Table 73 – Solution obtained for the dynamic and stochastic model

Model	Z						$T^*(Z^*)$	$T(Z)$	R	h	$R.h$
-	100	70	40	40	40	40	-	-	-	-	-
	120	120	60	40	40	40	-	-	-	-	-
Scenario	Z^*										
1	100	70	40	40	40	40	166.5	166.5	0.0	0.2	0.0
	120	120	60	40	40	40	318.8	318.8	0.0		
2	100	70	40	40	40	40	167.0	167.0	0.0	0.2	0.0
	120	120	60	40	40	40	289.4	289.4	0.0		
3	100	70	40	40	40	40	166.5	166.5	0.0	0.2	0.0
	120	120	60	40	40	40	328.6	328.6	0.0		
4	100	70	40	40	40	40	166.5	166.5	0.0	0.2	0.0
	120	120	60	40	40	40	328.3	328.3	0.0		
5	100	70	40	40	40	40	166.5	166.5	0.0	0.2	0.0
	120	120	60	40	40	40	333.1	333.1	0.0		
										Total regret	0.000

A myopic approach was also used to solve the dynamic and stochastic model for the same test instance. The generation of candidate solutions was also accomplished through the Add+Interchange algorithm (AIA). As explained in Subsection 2.3.2, the AIA starts with the solution found for the previous time period and, in successive iterations, selects the one-level airport upgrade change that allows the best improvement of the objective function, until no further improvement is feasible. Then, starting with the solution found, it selects the combination of feasible one-level capacity swaps that allow the best improvement of the objective function. The two procedures are repeated sequentially while solutions keep improving. For each candidate solution generated, the equilibrium is computed for the conditions of each scenario and time period, and is assessed in the light of the scenario-driven solutions. The solution obtained for the model through the myopic approach is presented in Table 74.

Table 74 – Solution obtained for the dynamic and stochastic model through myopic approach

Model	Z						$T^*(Z^*)$	$T(Z)$	R	h	$R.h$
-	80	80	40	40	40	40	-	-	-	-	-
	120	100	60	40	40	40	-	-	-	-	-
Scenario	Z^*										
1	100	70	40	40	40	40	166.5	167.0	-0.5	0.2	0.5
	120	120	60	40	40	40	318.8	315.7	3.1		
2	80	80	40	40	40	40	167.0	167.0	0.0	0.2	0.0
	120	100	60	40	40	40	289.4	289.4	0.0		
3	100	70	40	40	40	40	166.5	167.0	-0.5	0.2	0.6
	120	120	60	40	40	40	328.6	325.2	3.4		
4	100	70	40	40	40	40	166.5	167.0	-0.5	0.2	0.6
	120	120	60	40	40	40	328.3	324.7	3.6		
5	100	70	40	40	40	40	166.5	167.0	-0.5	0.2	0.6
	120	120	60	40	40	40	333.1	329.5	3.7		
										Total regret	2.398

According to the results obtained through the myopic approach, the airports in Centers 1 and 2 would be upgraded to Layout 4 ("two independent parallel runways") in the first time period. As for the second time period, the airports in Centers 1 and 2 would be upgraded to Layouts 6 and 5, respectively, and the airport in Center 3 would be upgraded to Layout 2 ("two close parallel runways"). With these improvements to the airport network, the expected regret, given by the sum of the regrets for the five scenarios affected by their weight, is 2.396.

5. Conclusion

This chapter expands the model presented in Chapter 2 by considering explicitly the dynamic and uncertainty issues inherent in airport network capacity expansion problems. Three models are proposed: 1) dynamic and deterministic model, which seeks the best schedule to perform improvements in an airport network for the demand and budget available in different time periods; 2) stochastic and static model, which considers different scenarios regarding demand, and determines the expansion actions to apply to the airport network in order to minimize the regret associated with each scenario-driven solution; and 3) dynamic and stochastic model, which considers both dynamic and stochastic characteristics of the two previous models, and determines the best schedule for the expansion actions to apply to an airport network in order to minimize total regret across the scenarios under consideration.

The three models proposed are very difficult to solve to exact optimality, because of their stochastic and/ or dynamic nature, and also as they combine the complexity of non-linear and mixed integer optimization models. Therefore, heuristic solution approaches are proposed for solving each model, based on the one proposed in Chapter 3 for solving the deterministic and static model. The solution approaches comprise two iterative procedures: (1) determination of capacity expansion actions to apply to the airport network (candidate solutions); (2) determination of equilibrium flows and travel costs within the airport network. The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the airports, and saves the best solution found during the search. The second procedure (lower-level) procedure determines the equilibrium traffic flows and costs in for the candidate solutions. It also determines the congestion taxes to apply in order to cancel out excess demand situations that might occur in some airport(s).

The solution approaches developed for solving the dynamic models (deterministic and stochastic) use the Simulated Annealing algorithm for generating candidate solutions, which encode tentative expansion actions to apply to the airports consistent with the budget available at each time period. The solution approaches to the stochastic models (static and dynamic variants) seek solutions which minimize expected regret, with regret being defined by the difference of total system throughput for the scenario-driven capacities (computed *a priori* by solving the correspondent deterministic variants of the models for the conditions of each scenario) and for the compromise capacities (determined by the models).

6. Appendix A: dynamic and stochastic *p*-median problem

Facility location models are important tools in the decision-making processes regarding the location, size and catchment area of public facilities. A vast body of literature deals with this subject (see e.g. Hansen et al. 1987, Daskin 1995, and Drezner 1995). The best-known location model is probably the *p*-median model, which seeks a maximum-accessibility solution for a specified number of facilities to be located (ReVelle et al. 1977, Mirchandani 1990). A possible formulation for the *p*-median problem is as follows.

$$\min \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} h_j d_{jk} Y_{jk} \tag{1}$$

subject to:

$$\sum_{k \in \boldsymbol{N}} X_k = p, \tag{2}$$

$$\sum_{k \in \boldsymbol{N}} Y_{jk} = 1, \quad \forall j \in \boldsymbol{N} \tag{3}$$

$$Y_{jk} \leq X_k, \quad \forall j, k \in \boldsymbol{N} \tag{4}$$

$$X_j \in \{0,1\}, \quad \forall j \in \boldsymbol{N} \tag{5}$$

$$Y_{jk} \in \{0,1\}, \quad \forall j, k \in \boldsymbol{N}. \tag{6}$$

The objective function (1) of the model expresses the minimization of the aggregate distance travelled by users to the assigned facilities, where $\boldsymbol{N}$ is the set of demand centers and potential facility (or candidate) sites, h_j is the demand at center j, d_{jk} is the distance between demand center j and potential facility site k, and Y_{jk} is binary variable equal to 1 if demand center j is assigned to site k, and 0 otherwise. Constraints (2) stipulate that exactly p facilities are to be located, where X_k is binary variable equal to 1 if a facility is located in site k, and 0 otherwise. Constraints (3) state that demand from all centers must be satisfied. Constraints (4) state that demand at center j cannot be assigned to a facility in site k unless a facility is located at k. Finally, constraints (5) and (6) state that the location and assignment variables are binary.

This formulation to the p-median problem is static and deterministic, as it takes constant, known quantities as inputs (e.g. demand and costs, obtained through forecasts) and derives a single solution to be implemented at one point in time. While such static and deterministic model can provide interesting insights into facility location decisions, it does not capture important aspects of real-world problems. In fact, the investments required for locating or relocating facilities is usually large, and thus facilities are expected to remain open for a longtime period. During the facilities' lifetime, decision parameters, such as demand and cost, may change dramatically. This calls for models that address the dynamic and stochastic issues inherent in facility location problems. These issues have been the concern of a growing number of studies. Stochastic models seek for solutions that take into account the randomness of parameters. Dynamic models seek solutions which will effectively serve changing demand over time, and considers the timing of facility openings and expansions over the design period under consideration.

On stochastic planning, scenario models consider a set of possible future variable values, obtained through a quantitative characterization of the values that the problem input parameters may take, with the likelihood of each scenario occurring previously determined, and the objective is to find solutions which perform well under all scenarios. A common approach in scenario planning is to optimize the average case or the worst case performance over all the scenarios. However, such approaches may result in underused or overused facilities for most of the time. Other approaches are those of Sheppard (1974), who developed a model which seeks to minimize the expected cost over all scenarios, Schilling (1982), in which the initial location for the facilities are those that are common across the optimal locations for most scenarios, and Daskin et al. (1992), who proposed a forecast horizon-based approach. Other scenario planning approaches use the concept of regret, being regret defined for each scenario and given by the difference between the objective function values for the overall solution (called compromise solution) and the optimal solution for that single scenario (had planners known for certain the scenario would occur). Ghosh and McLafferty (1982) proposed a model that minimizes the sum of the regrets or the sum of the squared regrets over all scenarios, and Daskin et al. (1997) proposed a model called the α-reliable p-median minimax regret model, which seeks solutions that minimize the maximum regret with respect to a set of scenarios under consideration. Another commonly used criterion is the minimization of the expected regret, given by the sum of the weighted regrets for all scenarios with their probability or weight (Owen and Daskin, 1998).

Dynamic facility location problems have been the scope of several studies since the pioneering work of Roodman and Schwartz (1975), who developed a model for determining the schedule for closing facilities in order to minimize total discounted costs (costs include fixed and variable operating costs for the opened facilities, costs for closing facilities, and transportation costs), and of Roodman and Schwartz (1977), which improved the previous study by also considering the possibility to open new facilities. Dynamic planning has then received several contributions, namely from Van Roy and Erlenkotter (1982), and Fong and Srinivasan (1981). A more recent study from Current et al. (1997) incorporates both dynamic and stochastic issues on an optimization model which seeks the location an initial number of facilities when the final number of facilities to be located is unknown. This study uses the general concept of ‘state of nature’, which can either represent a scenario or a constraint to the number of facilities to locate in different stages. Two objectives are considered: minimization of maximum regret across the set of scenarios under consideration and the minimization of the expected opportunity loss.

Following the work of Current et al. (1997) and Serra et al. (1996), which also developed an approach based on the concept of expected regret, a possible formulation for the dynamic and stochastic *p*-median problem is as follows.

$$\min \sum_{s \in \boldsymbol{S}} w_s \, R_s \qquad (7)$$

subject to:

$$R_s - \left[D_s\left(X_{kt}, Y_{jkts}, p_t\right) - D_s^*\left(X_{kts}^*, Y_{kts}^*, p_t\right)\right] = 0, \ \forall s \in \boldsymbol{S} \tag{8}$$

$$\sum_{j \in \boldsymbol{N}} X_{jt} = p_t, \ \forall t \in \boldsymbol{T} \tag{9}$$

$$\sum_{k \in \boldsymbol{N}} Y_{jkts} = 1, \ \forall j \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T}, \ \forall s \in \boldsymbol{S} \tag{10}$$

$$Y_{jkts} \leq X_{kt}, \ \forall j,k \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T}, \ \forall s \in \boldsymbol{S} \tag{11}$$

$$X_{kt} \geq X_{kt-1}, \ \forall j \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \setminus \{t=1\} \tag{12}$$

$$X_{jt} \in \{0,1\}, \ \forall j \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T} \tag{13}$$

$$Y_{jkts} \in \{0,1\}, \ \forall j,k \in \boldsymbol{N}, \ \forall t \in \boldsymbol{T}, \ \forall s \in \boldsymbol{S}. \tag{14}$$

The objective function (7) represents the minimization of the expected regret across the scenarios under consideration, where w_s and R_s stand for the probability (or weight) and regret associated to scenario s, respectively. Constraints (8) state that the regret associated to scenario s is given by the difference of the aggregate distance D_s for the compromise locations (X_{kt}, which are determined by the model) and the aggregate distance D^*_s for the scenario-driven locations (X^*_{kt}, which are solutions for the dynamic and deterministic p-median model for the conditions of each scenario). The aggregate distance for scenario s for the compromise locations and for the scenario-driven locations can be written in the following way:

$$D_s\left(X_{kt}, Y_{jkts}, p_t\right) = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{t \in \boldsymbol{N}} h_{jts} d_{jk} Y_{jkts}, \ \forall s \in \boldsymbol{S}, \text{and}$$

$$D_s^*\left(X_{kts}^*, Y_{jkts}^*, p_t\right) = \sum_{j \in \boldsymbol{N}} \sum_{k \in \boldsymbol{N}} \sum_{t \in \boldsymbol{N}} h_{jts} d_{jk} Y_{jkts}^*, \ \forall s \in \boldsymbol{S},$$

where X_{kt} is a binary variable equal to 1 if a facility is located in site k at time period t, and 0 otherwise, Y_{jkts} is a binary variable equal to 1 if demand center j is assigned to site k at time period t for scenario s, and 0 otherwise, and p_t is number of facilities to be located at time period t (variables X^*_{kt} and Y^*_{jkts} have the same meaning, but are associated to the scenario-driven locations). Constraints (9) stipulate that exactly p_t facilities are to be located at time period t. Constraints (10) state that each demand center must be assigned to exactly one facility in each scenario and time period. Constraints (11) state that demand at center j cannot be assigned to a facility in site k under scenario s at time period t unless a facility is located at k. Constraints (12) state that facilities cannot be closed from a time period to the next. Constraints (13) and (14) state that the location and assignment variables are binary.

The scenario-driven locations and (least-cost) assignments are determined by solving the corresponding dynamic and deterministic p-median model for the conditions of each scenario. The dynamic and stochastic model can be easily transformed into a dynamic and deterministic model by suppressing Constraints (8) and the scenario index s. The binary location and assignment variables for the compromise locations are replaced with the corresponding scenario-specific location and assignment variables, X^*_{kt} and Y^*_{jkts}. The objective-function is naturally defined by the minimization of the demand weighted total distance for the scenario specific demand values:

$$\min \sum_{j\in N} \sum_{k\in N} \sum_{t\in N} h_{jt} d_{jk} Y^*_{jkt} .$$

The dynamic and stochastic *p*-median model was solved for a randomly generated test instance with 4 demand centers (seed #1), which are assumed to be the possible facility sites. The location of the centers was randomly generated over a square-shaped region with 300 km of size. Two time periods were considered ($\boldsymbol{T} = \{t_1, t_2\}$), where the demand from the centers in each time period was defined as follows. For time period t_1, the demand from each center was assumed to be deterministic, and was randomly generated over the interval [30, 100] users. For time period t_2, the demand from each center was obtained assuming an increase in the interval [-25%, 25%], to which a stochastic parcel, dependent upon the center and the scenario, and randomly generated in the interval [-25%, 25%], was added (in the limit, the demand from a center in t_2 can increase 50% with respect to the demand in t_1, or decrease by 50%, with equal probability). Four scenarios were considered for time period t_2. The coordinates and demand values at each time period for the scenarios considered are given in Table 75. The Euclidian distances between centers are given in Table 76. It was assumed that one facility must be located in the first time period, and another facility in the second ($p_t = \{1, 2\}$). The model was programmed and solved within the optimization package FICO Xpress-MP.

Table 75 – Coordinates and demand of the centers

Center	X (km)	Y (km)	$h(t_1)$ (users)	$h(s_1,t_2)$ (users)	$h(s_2,t_2)$ (users)	$h(s_3,t_2)$ (users)	$h(s_4,t_2)$ (users)
1	115	196	36	41	41	44	29
2	20	217	83	80	106	80	90
3	201	115	67	54	50	58	70
4	189	265	95	99	62	107	92

Table 76 – Euclidian distances between centers (km)

Center	1	2	3	4
1	0	97	118	102
2	97	0	208	176
3	118	208	0	151
4	102	176	151	0

The scenario-driven solutions obtained are represented in Figure 53 to Figure 56 for time periods t_1 (left) and t_2 (right). The white labels represent demand centers with no facilities installed; the black labels represent demand centers where the facilities are located; and the grey labels contain the demand values. Solutions are also described in Table 77. At time period t_1, the candidate site 1 is chosen for scenarios s_1, s_1 and s_3, because, despite being the smallest center, is in a central position and can thus serve well the demand from the other centers. The demand weighted total distance for these three scenarios is 25,663 users×km (note that demand is the same for all scenarios at time period t_1). For scenario s_4, the facility is located in site 4, which, despite being the largest demand center, and thus reducing the aggregate distance as users from this center do not travel, is not in a good position to serve the remaining centers. This happens because center 1 loses demand at time period t_2, and the excentric located centers 2 and 4 gain importance, making it preferable in aggregate terms to reduce the distance travelled by the users of these centers. Demand at center 1 is higher for the remaining scenarios, still making it a good location for serving well the remaining centers. The location of the second facility differs depending on where demand is more: for scenarios s_1 and s_3 the facility is best located in center 4, whereas for scenario s_2 it is best located in center 2. The feasible solutions for the problem shown in Table 78 support the above discussion.

Assuming that all scenarios are equally probable (w_s = 1/S = 0.25), the model locates one facility in site 4 at time period t_1, and another facility in site 2 at time period t_2, minimizing the expected regret to 961[1]. The assignments for each scenario under the compromise locations obtained by the model are given in Figure 57 to Figure 60. Since the objective is to minimize expected regret, the model assigns demand centers to the closest facilities in order to reduce weighted distance (in the limit, the expected regret equals zero if the weighted distance equals the sum of the weighted distances for all scenario-specific solutions). Therefore, as there are no capacity constraints for the facilities, the only difference between solutions is the demand assigned to facilities.

[1] 0.25*(40,530-39,837) + 0.25*(39,926-37,889) + 0.25*(41,425-40,310) + 0.25*(41,777-41,777) = 961

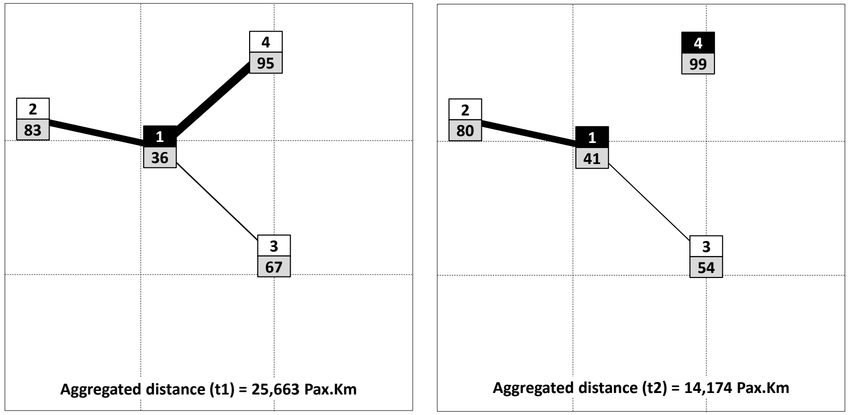

Figure 53 – Optimal locations and assignments for scenario s_1

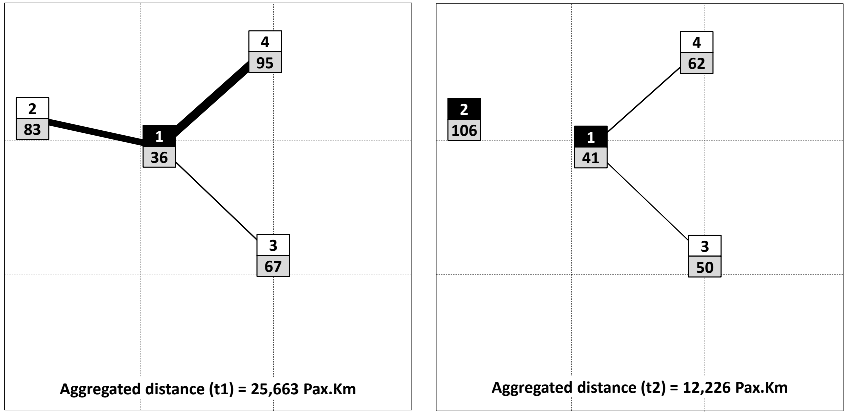

Figure 54 – Optimal locations and assignments for scenario s_2

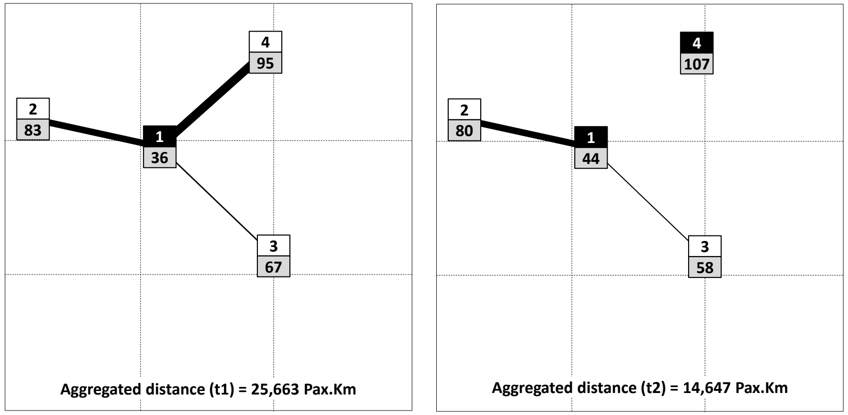

Figure 55 – Optimal locations and assignments for scenario s_3

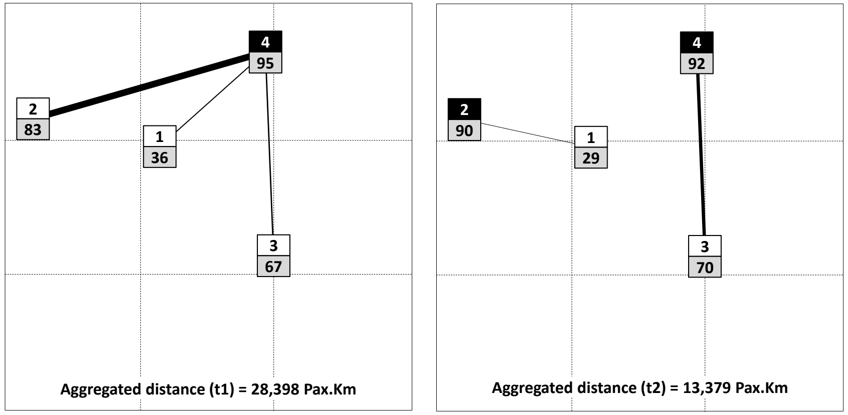

Figure 56 – Optimal locations and assignments for scenario s_4

Table 77 – Solutions of the dynamic and deterministic model for each scenario-specific conditions considering p_t = {1, 2}

Scenario	*X (t1)*				*V* (t1)*	*X (t2)*				*V* (t2)*	*V**
	1	2	3	4		1	2	3	4		
s1	1	-	-	-	25,663	1	-	-	1	14,174	39,837
s2	1	-	-	-	25,663	1	1	-	-	12,226	37,889
s3	1	-	-	-	25,663	1	-	-	1	14,647	40,310
s4	-	-	-	1	28,398	-	-	-	1	13,379	41,777

Table 78 – Admissible solutions of the dynamic and deterministic model for each scenario-specific conditions considering p_t = {1, 2}

X (t1)				*V* (t1)*	*X (t2)*				*V* (t2)*				*V**			
1	2	3	4	*s1, s2, s3, s4*	1	2	3	4	*s1*	*s2*	*s3*	*s4*	*s1*	*s2*	*s3*	*s4*
1	-	-	-	**25,663**	1	1	-	-	16,461	12,226	17,748	17,645	42,124	**37,889**	43,411	43,308
1	-	-	-	25,663	1	-	1	-	17,841	16,607	18,655	18,102	43,504	42,270	44,318	43,765
1	-	-	-	25,663	1	-	-	1	14,174	16,227	14,647	17,041	**39,837**	41,890	**40,310**	42,704
-	1	-	-	34,175	1	1	-	-	16,461	12,226	17,748	17,645	50,636	46,401	51,923	51,820
-	1	-	-	34,175	-	1	1	-	18,920	13,339	20,419	16,698	53,095	47,514	54,594	50,873
-	1	-	-	34,175	-	1	-	1	**12,132**	**11,528**	**13,027**	**13,379**	46,307	45,703	47,202	47,554
-	-	1	-	35,852	1	-	1	-	17,841	16,607	18,655	18,102	53,693	52,459	54,507	53,954
-	-	1	-	35,852	-	1	1	-	18,920	13,339	20,419	16,698	54,772	49,191	56,271	52,550
-	-	1	-	35,852	-	-	1	1	18,270	22,853	18,575	18,813	54,122	58,705	54,427	54,665
-	-	-	1	28,398	1	-	-	1	14,174	16,227	14,647	17,041	42,572	44,625	43,045	45,439
-	-	-	1	28,398	-	1	-	1	12,132	11,528	13,027	13,379	40,530	39,926	41,425	**41,777**
-	-	-	1	28,398	-	-	1	1	18,270	22,853	18,575	18,813	46,668	51,251	46,973	47,211

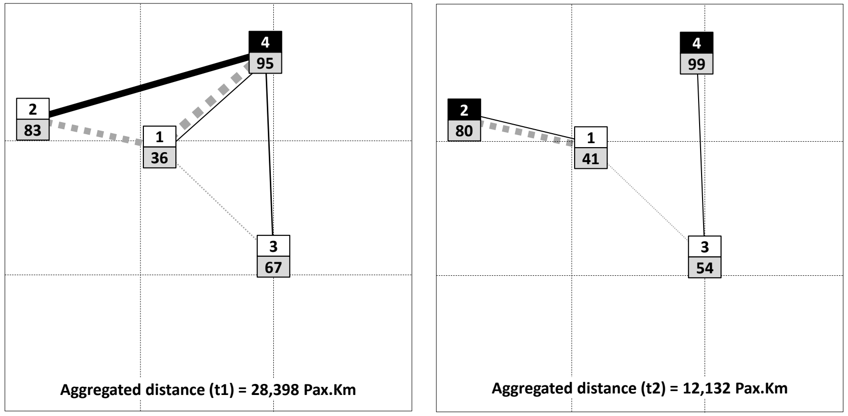

Figure 57 – Optimal compromise locations and assignments for scenario s_1

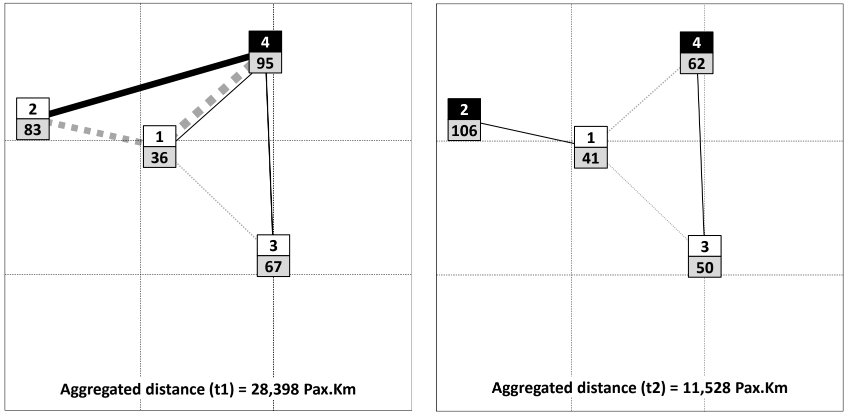

Figure 58 – Optimal compromise locations and assignments for scenario s_2

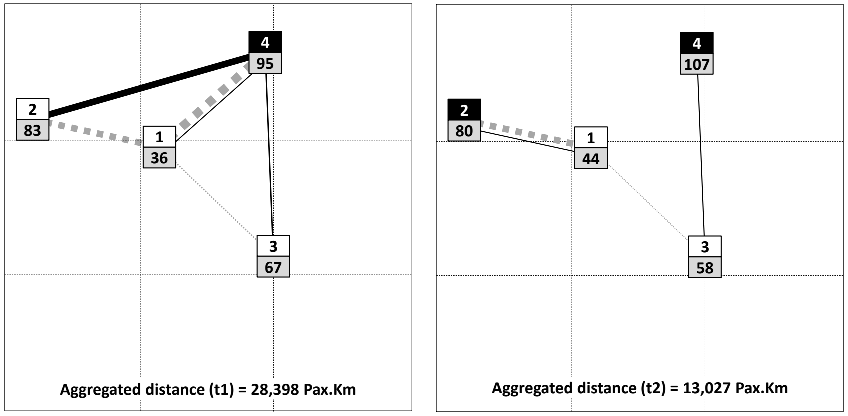

Figure 59 – Optimal compromise locations and assignments for scenario s_3

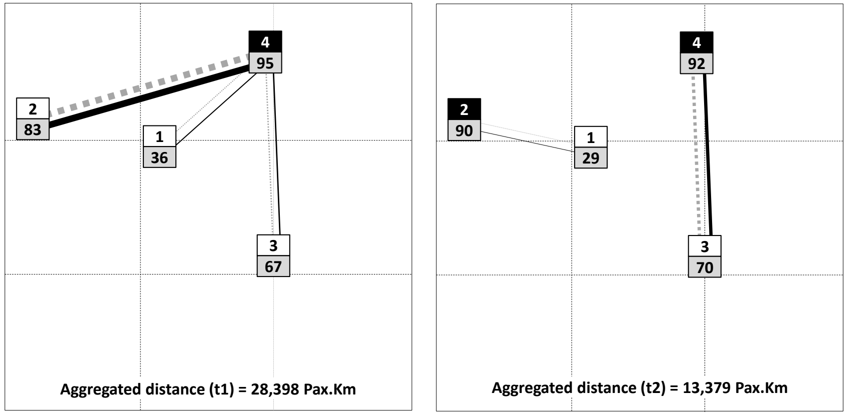

Figure 60 – Optimal compromise locations and assignments for scenario s_4

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Chapter 7

Conclusion

This thesis addressed the strategic planning of airport expansion and construction in the context of airport networks. The problem dealt with, analyzed from the perspective of aviation authorities, was to determine the improvements to implement in an airport network in order to satisfy future demand in the best possible way, given budget limitations. The major contribution of this thesis is the development of decision-aid tools, specifically optimization models, which can be used by aviation authorities in the processes within which this kind of decisions are made – as stated in Chapter 1, this was precisely the main objective of the thesis.

The models proposed - in Chapters 2, 5 and 6 - apply to a set of metropolitan areas, and determine which airports should receive additional capacity and where new airports should be built, in order to maximize total system throughput (maximization of "demand coverage"). The models take into account the impact of expansion decisions on travel costs and on the demand for air travel. This is accomplished by assuming that:

(1) the travel cost incurred by passengers includes an airport-related cost, which increases with the airports utilization rate (as an airport becomes congested, the airport operating costs and waiting times increase), thus increasing capacity reduces travel cost; (2) traffic flow decreases with travel cost, thus the decrease in travel cost due to capacity enhancements leads to an increase in traffic flows (origin/destination traffic, and/or connecting traffic diverted from congested hub airports).

The interactions between travel costs and traffic flows presuppose the existence of equilibrium within the airport network. Two important attributes of the models regarding this equilibrium are: (1) travel cost decreases with the traffic flow in the flight legs because of economies of scale (as opposed to diseconomies of scale in the airports); (2) travel cost may include a congestion tax levied by the aviation authority to regulate the utilization of airports (in its absence, excess demand situations could occur and airports would be able to make “unfair” profits).

The model described in Chapter 2 is the basic model in the sense that is the foundation for the models presented in the following sections. It applies to a set of metropolitan areas served by airports or multi-airport systems (multi-airport systems are modeled as single airports with equivalent capacity), and determines the best set of (discrete) expansion actions to apply to the metropolitan areas. Expansion actions consist of increasing the number or changing the location of runways at existing airports, and of improving terminal buildings and apron areas.

The model described in Chapter 5 also applies to a set of metropolitan areas, but, unlike the basic model, can either be served by an airport/multi-airport system, or not – it is a location model in addition to being a capacity expansion model. Hence, expansion actions may consist of expanding an existing airport and of building a new airport in metropolitan areas which are presently not served by an airport (provided it will serve a given minimum traffic amount). Moreover, this model considers explicitly the complementarity and competition between air travel and land travel modes (such as car, train or bus). This is accomplished through the consideration of mode choice decisions. For instance, a passenger may use only air transportation to travel between the origin and destination cities (if served by airports), by one of the land modes (if a direct connection exists), or by combining two or more modes in her/his trip. This makes it possible to consider the response of travelers behavior to congestion problems at the airports, which can, for instance, switch to other travel modes with lower travel cost.

The models described in Chapter 6 deal with the dynamic and/or uncertainty issues inherent in airport network capacity expansion problems. Three models are proposed. The first model is deterministic, as it takes constant, known quantities as inputs (e.g. demand, travel costs and capacity over time), but, instead of looking for a single solution to be implemented at one point in time, it seeks the best schedule to perform improvements in the airport network for the demand and budget available in different time periods. The second model focuses on a single time period, but considers different scenarios regarding demand, and determines the expansion actions to apply to the airport network in order to minimize the expected regret across a set of scenarios under consideration. The third model considers both the dynamic and stochastic characteristics of the two previous models, and determines the best schedule for the expansion actions to apply to an airport network in order to minimize expected regret.

The second objective of this thesis was to develop efficient techniques to solve the models. With regard to this objective, a heuristic solution approach was proposed in Chapter 3 to solve the basic model. The approach comprises two iterative procedures: (1) determination of capacity expansion actions (candidate solutions), and (2) determination of equilibrium flows and travel costs in the network. The first (upper-level) procedure establishes and evaluates, in each iteration, tentative expansion actions for the airports consistent with the budget available, and saves the best solution found during the search (that is, the solution that yields the largest system throughput). The second procedure (lower-level) procedure determines the equilibrium traffic flows and costs for each tentative expansion action. The lower-level procedure also encompasses the determination of the congestion taxes to apply in order to cancel out excess demand situations that might occur in some airport(s).

The simulation of the equilibrium traffic flows and travel costs within the airport network was performed using the Method of Successive Averages. The application of this method to a large sample of randomly generated test instances showed that it provided the same equilibrium pattern regardless of the initial solution considered. The computation of the congestion taxes to apply to the airports was done using the Line Search Method. The results obtained through this method were assessed in the light of the ones obtained by a local search algorithm. The Line Search Method was proven to provide the best results with less computation effort for all test instances.

Several heuristic algorithms were proposed to generate the tentative expansions actions to apply to the airport network (candidate solutions) within the upper-level component of the solution method. Specifically, we developed classic local search algorithms (Add and Interchange, and Drop and Interchange), variable neighborhood search algorithms (Classic Variable Neighborhood Search Algorithm, Variable Neighborhood Descent Algorithm, and Exhaustive Variable Neighborhood Descent Algorithm), and genetic algorithms (Classic Genetic Algorithm and Hybrid Genetic Algorithm). The algorithms were then compared from the standpoint of solution quality and computation effort through their application to a sample of randomly-generated test instances of different sizes. The Hybrid Genetic Algorithm was proven to provide the best solutions for almost all test instances, but at a huge computational effort. The Add and Interchange and the variable neighborhood search algorithms also provided good results, and were relatively fast to solve the model even for larger instances.

For solving the dynamic and stochastic models presented in Chapter 6, we proposed heuristic solution approaches based on the one presented in Chapter 3 for solving the deterministic and static model. The solution approaches developed for solving the dynamic models (deterministic and stochastic) use the Simulated Annealing algorithm for generating candidate solutions, which encode tentative expansion actions to apply to the airports consistent with the budget available at each time period. The solution approaches to the stochastic models (static and dynamic variants) seek solutions which minimize expected regret, with regret being defined by the difference of total system throughput for the scenario-driven capacities (computed *a priori* by solving the correspondent deterministic variants of the models for the conditions of each scenario) and for the compromise capacities (determined by the models).

The third objective for this thesis was to apply the models to appropriate case studies. With regard to this objective, two applications to real networks are presented in Chapters 4 and 5.

Chapter 4 presents an application of the basic model (described in Chapter 2) to determine the long-term developments of the main airport network of the US. The study focused on the 28 metropolitan areas containing the 34 airports identified in the Federal Aviation Administration's Operational Evolution Plan (OEP). These airports handle a large share of the country's overall traffic, and, therefore, an inadequate throughput at these airports may constrain the whole airport network. In order to capture the dynamics of demand around multi-airport systems, the main secondary airports serving those metropolitan areas were also considered. The statistical calibration of the model's parameters was performed by the Nelder-Mead method using data for the average day of the first quarter of 2008. The calibration results obtained were credible since, overall, the modeled traffic flows matched observations quite reasonably. The 10th peak day of operations of 2030 was used as the reference situation for the study. The results obtained through the model were globally consistent with the recommendations of the FACT 2 study conducted by the FAA to identify the long-term capacity needs of the main airports of US.

The study addressing the long-term capacity needs of the main airport network of the U.S. was carried out from a policy-level, macroscopic perspective. Our purpose was essentially to demonstrate that the optimization model upon which the study was based can be useful to support analyses of the evolution of airport networks and to provide insights into the best way of expanding them. However, the possible expansion actions applicable to the airports were defined in a very approximate way. It must also be emphasized that, similarly to the FACT 2 study, we did not take into account the expected impact of NextGEN interventions on the performance of the US airport network. These measures are supposed to lead to substantial capacity increases, thus reducing the need for capacity expansion actions.

Chapter 5 presents the results of a study whose purpose was to provide some insights regarding the expansion of the main airport network of Germany. This study was based on a model which takes explicitly into account the competition and complementarity among transport modes. This is important since Germany has good high-speed rail and road networks connecting its main airports and metropolitan areas, which, on the one hand, compete with air transport for demand, even for medium- and long-haul O-D markets, and, on the other hand, feed the airport network (this is not the case of the US, where the metropolitan areas are in most cases too far away for land transport to be a viable alternative to air transport). A heuristic algorithm based on the one presented in Chapter 3 was developed to solve the model. The statistical calibration of the model's parameters was also performed by the Nelder-Mead method. The average day of 2009 was used as reference situation for the calibration of the model parameters. The traffic flows obtained through the calibration matched the observed values quite reasonably. The results obtained by the model for a reference peak day of 2030 were consistent with a study developed by the European Center for Aviation Development (ECAD) regarding the future capacity needs of the German main airports.

Overall, the objectives set forth for this thesis were, in the author's view, successfully achieved. This does not mean that it is not possible to improve on the work done – e.g. augmenting the models with equity and robustness objectives in order to tackle two types of concerns that aviation authorities are usually sensitive to. Also, both the US and the Germany case studies can be enriched, for example with analyses of the impact of advances in air traffic control systems expected in the future on the capacity expansion needs of the airport networks of both countries. In the future, we hope to be able to accomplish these and other improvements, which does not seem too difficult given the position from where we will start.

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