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ORIGINAL PAPER

How does fuel price uncertainty affect strategic airline planning?

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Abstract Today, jet fuel costs are a growing part in airlines' expenditures and have high fluctuations. Therefore, airlines think about minimizing jet fuel costs and counteracting fuel price uncertainty. The strategic flight planning highly determines the jet fuel consumption of an airline. In this paper, we present a study of the impacts of fuel price uncertainty on strategic flight planning. The study is performed with a new developed stochastic optimization model for strategic flight frequency planning under jet fuel price uncertainty. As airline seats are a perishable service, we also consider uncertain demands. We present a two-stage stochastic program that determines the optimal offered flights with their frequency, and uses the passenger routes for evaluation. As innovation, this study integrates financial hedging and operational risk management simultaneously to decrease the solutions' risk. We show that the optimal offered flights depend on the jet fuel price development. Finally, the integration of financial planning into the operational model improves profit at given risk levels of the airline and dominates non-integrated planning.

Keywords Schedule design · Strategic airline planning · Stochastic programming · Jet fuel price uncertainty · Financial hedging

1 Introduction

Today, the two largest parts of the expenditures of airlines are the costs for labor and fuel (Air Transportation Association—Office of Economics 2009). The percentage for jet fuel expenditures has increased in the last years. They have grown from

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approx. one-tenth to one-third in only 10 years (Deutsche Bank Research 2008). As jet fuel price fluctuations are also high (see Fig. 2), airlines face a growing uncertainty for their costs. It therefore becomes more important for airlines to think about minimizing fuel costs and counteracting fuel price uncertainty.

As the schedule design significantly determines the fuel consumption of an airline, we aimed to develop a model that supports strategic decisions about this planning phase under fuel price uncertainty. We determine the optimal offered flights between a given set of airports with their frequency. To counteract jet fuel price uncertainty, we consider financial hedging instruments. As demand is highly uncertain at the time when the schedule is planned and aircraft seats are one of the most perishable services, we also introduce stochastic demands.

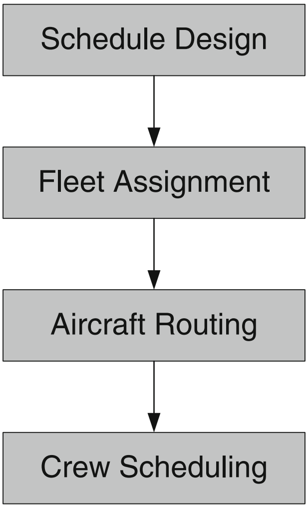
This paper is organized as follows: Sect. 2 introduces schedule planning, presents the cost structure in the airline industry and discusses methods to counteract fuel price uncertainty. It also discusses risk management, briefly introduces demand uncertainty and ends with a literature survey. Section 3 deals with the proposed model: It presents a model description and the mathematical model before it shows the data used for the case study. Section 4 displays the results for model variations with and without jet fuel price uncertainty and finally, a conclusion is drawn in Sect. 5.

2 Problem description

2.1 Schedule planning in the airline industry

An airline schedule is usually planned several months in advance in several separate steps. Figure 1 gives an overview over these steps:

Fig. 1 Planning stages



The first step is to decide which flights are offered to the customers. For example a number of three flights from Frankfurt to London every day in the morning could be offered. This step is called schedule design and is usually done manually. The traffic forecast, seasonal demand as well as strategic and tactical initiatives are important for this first step. After the schedule design, the fleet assignment takes place. This step assigns aircraft types to the flights to match the demand. The next planning step is the aircraft routing. This step assigns the particular airplanes of an airline to the flights, so that every flight is covered and adequate opportunities and time for maintenance is reserved. Finally, crews are assigned to the flights in the crew scheduling. After these planning steps, operating departments take care of conforming the schedule and restoring it in case of deviations, e.g. due to bad weather (see Gopalan and Talluri 1998; Barnhart and Cohn 2004).

In this paper, we focus on the schedule design phase and develop a strategic planning model for the airline industry under jet fuel price and demand uncertainty. Similarly to Lederer and Nambimadom (1998) we mean by schedule the frequency of service between two airports. We therefore determine if and how often a flight between two airports should be flown with a certain aircraft type and how much fuel should be hedged as a decision under uncertainty. The optimal passenger flow in each scenario enables the evaluation. The flight times are not determined as this model aims to support decisions on a strategic level and focuses on uncertainty. To measure the robustness of the solutions, we integrate and restrict the Conditional Value at Risk (CVaR) as risk measure.

Although the flight schedule of an airline depends on other factors as well, the study will give some insight into the impacts of fuel price uncertainty on strategic airline schedule planning. We only consider the most important aspects of schedule design, because we aim to focus on uncertainties. Thereby we can integrate fuel price and demand scenarios and keep the model smaller and solvable.

2.2 Cost structure in the airline industry

The Air Transportation Association—Office of Economics (2009) analyzes the current cost structure of North American airlines. The two largest parts of the expenditures of airlines are the costs for labor and for fuel. The Deutsche Bank Research (2008) underlines that the percentage of expenditures for jet fuel prices has become an increasing part of the total expenditures: They grew from approx. 10 % in 1998 to approx. 33 % in 2008. For some low-cost carriers the jet fuel expenditures are even about 50 % of their total expenditures.

2.3 Jet fuel price uncertainty

The Energy Information Administration (2009) provides data for oil and fuel prices (see Fig. 2). The data shows that the price for jet fuel has high fluctuations and increases.

Airlines thus have to face a high uncertainty for a growing part of their expenditures.

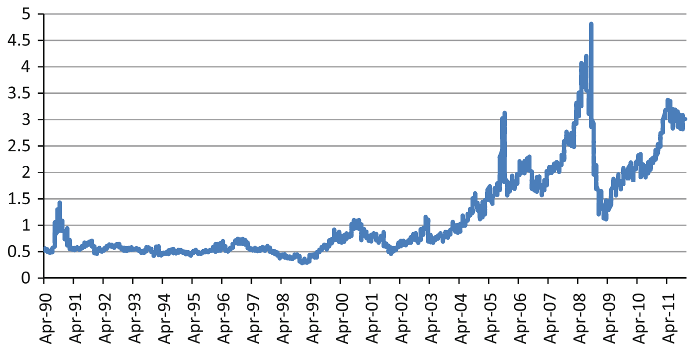


Fig. 2 Jet fuel price development 1986–2009. Gulf Coast Kerosene-Type Jet Fuel Spot Price FOB (Dollars per Gallon) [Data: Energy Information Administration (2009)]

2.4 Counteracting higher jet fuel prices and fluctuation

Larger aircraft usually have less jet fuel consumption per passenger (see Air France Press Office 2008). The airbus A380 is the first long-haul aircraft that consumes <3 l per passenger over 100 km. But using larger aircraft is only beneficial when there are enough passengers. Therefore, it might be necessary to route passengers through hubs and to merge flights. For example if there are several flights from Europe to North America, the passengers from all the European locations could first be flown to London, and one flight with a larger aircraft from London to North America could save jet fuel. On the other hand, this means less comfort for the European passengers who do not start in London, because they have to change the plane. Some possible passengers might then choose another airline that offers a non-stop-flight from their hometown. The airline could also offer a discount as compensation for the discomfort. This tradeoff between reducing passenger comfort, which might decrease revenues, and reducing jet fuel consumption is considered in this paper.

It is also possible to pass the higher jet fuel costs to the passengers via fuel surcharges. To consider that, the model could be solved with other demand and price data that could be calculated from a revenue management framework.

To counteract high jet fuel price fluctuations financial hedging instruments can be used. With financial hedging the price for future purchases can be fixed. If an airline wants to hedge against higher jet fuel prices, it can sign a contract that fixes the price for jet fuel for a certain amount for a certain time. Then higher fuel prices do not have negative effects on the airline, but the airline is also not able to benefit from lower jet fuel prices anymore. Financial hedging instruments can be used to minimize fluctuations and are therefore an effective method for risk management.

2.5 Derivatives and hedging of jet fuel prices

Derivatives, as Hull (2003) argues, have become increasingly important in the last years. Today, futures, forward-contracts, options and swaps are regularly traded.

Their value depends on other underlying variables, for example traded assets or currencies.

The easiest hedging instruments are forward-contracts and futures. Those are contracts to buy or sell a certain asset to a certain price at a certain time. Forward-contracts are usually traded in the over-the-counter market whereas futures are standardized and usually traded on an exchange. For example the future price of gold in September for December could be quoted as $300. This is the price for which traders could buy or sell gold for delivery in December. The contract specifies the amount, the price and, in case of a commodity, also the product quality and delivery location. Contracts are usually available for several delivery periods in the future.

Options are a different type of derivatives. They give the owner the right to do something but, in contrast to forward-contracts and futures, they need not to be exercised. They also have a price, whereas it costs nothing to enter into a forward or future contract.

Cobbs and Wolf (2004) argue that futures or forward-contracts for jet fuel are often not available, but show dynamic hedging strategies to hedge the jet fuel price using derivatives with other underlying assets like crude or heating oil, whose prices highly correlate with the jet fuel price.

With an industry survey Cobbs and Wolf (2004) show that hedging was at the end of 2003 not very common at the majority of airlines. Their research results indicate that hedging creates market value and that the consideration of financial hedging instruments therefore could create a competitive advantage for an airline.

In general, a good risk management strategy can be beneficial for companies. Triantis (2005) lists several reasons.

2.6 Demand uncertainty

Airlines do not only face uncertainty for their costs: The demands and therefore the revenues are also uncertain. Figure 3 shows the yearly growth of global passenger traffic from 1951 to 2007 [Data see Air Transportation Association (2010)]. Cento (2009) argues that because the product of airlines is one of the most perishable, they have implemented techniques to counteract demand uncertainty: For short-term demand fluctuations the yield management is an efficient method, but to counteract long-term demand shifts the strategic network planning has to be adjusted.

The variations in the particular regions are even higher: The International Air Transport Association reports that the growth in passenger demand in March 2009 varies between 4.7 % for the Middle Eastern carriers and −15.6 % for the African carriers. Furthermore, the average load factor decreased because capacity was not adjusted as much as demand fell [Data see International Air Transport Association (2009b)]. As this paper intends to focus on strategic planning, the demand uncertainty also has to be considered.

2.7 Underlying literature

The airline industry is a sector where operations research is widely used. In this section, we give a short overview about the literature that is related to this paper. Yu

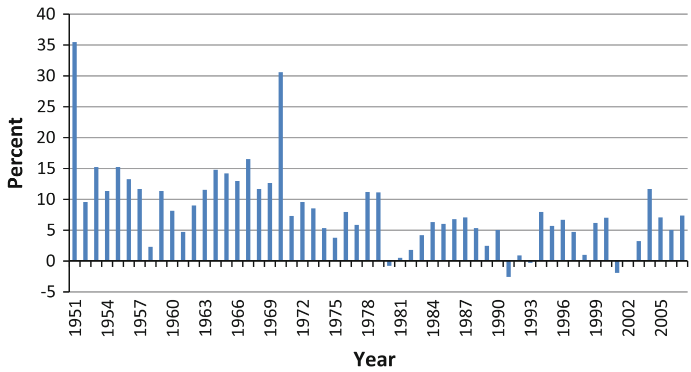


Fig. 3 Growth of global passenger traffic

(1998) presents a wide variety of operations research applications in the airline industry.

Gopalan and Talluri (1998) give an overview over problems and mathematical models in airline schedule planning. Furthermore Etschmeier and Mathaisel (1985) present an overview of early literature dealing with schedule construction and schedule evaluation. Lederer and Nambimadom (1998) show that different network configurations such as hub or direct networks can be optimal in different situations.

In Sect. 2 of their paper, Wen and Hsu (2006) review the literature on airline flight frequency programming models. These models can also include several fleet types. Like in the developed model in this paper, the main decision variables are the flight frequencies on routes with different aircraft types.

Sherali, Bish and Zhu (2006) present a survey of models, concepts and algorithms for the fleet assignment problem. They consider various types of pure fleet assignment models as well as integrated fleet assignment models with other planning phases. An integrated model for fleet assignment and schedule design that considers flight leg selection is presented by Lohatepanont and Barnhart (2004). They also give a short overview over integrated models for schedule design and fleet assignment. Soumis, Ferland and Rousseau (1980) present an integrated model that considers passenger satisfaction and the interaction between passenger and aircraft routing.

Cobbs and Wolf (2004) describe hedging strategies for airlines and perform an industry survey. They find out that the airline industry is not very much hedged at the time of their survey, although this would give a competitive advantage. Also Carter, Rogers and Simkins (2006) find out that hedging is positively related to the firm value of airlines. Triantis (2005) presents general reasons for an integrated risk management strategy. Financial hedging instruments are described by Hull (2003).

Demand uncertainty has also been considered in strategic airline planning. For example Barla and Constantatos (1999) present reasons why hub-and-spoke networks provide more flexibility to counteract uncertain demand. Barla (1999) examines with a duopoly game the effects of strategic interactions on an airline network under demand uncertainty.

Hsu and Wen (2000) apply Gray Theory to the airline network design problem and consider demand uncertainty. The same authors (Hsu and Wen 2002) evaluate the airline network design in response to demand fluctuations. Thereby they also review the literature that considers demand uncertainty. Yan, Tang and Fu (2008) present an airline scheduling model that considers stochastic demands, while Sherali and Zhu (2008) provide a stochastic model for fleet assignment considering stochastic demands. List et al. (2003) present a stochastic model for fleet planning under uncertainty and consider partial moments as a measure for robustness. Fábián (2008) shows how the CVaR can be integrated into linear optimization models.

For the used optimization techniques and their terms we refer to detailed introductions in literature: Kall and Wallace (1994) and Birge and Louveaux (1997) provide detailed introductions in stochastic programming.

To the knowledge of the authors, a strategic planning model for airline schedule design that considers risk measures and financial hedging under jet fuel price and demand uncertainty has not been developed yet.

3 Model

3.1 Model description

This section presents the developed mathematical optimization model that determines the optimal flights offered with their frequency and the optimal passenger flows for a given network of airports. The passengers can be directly transported to their destination on a non-stop flight or they can be indirectly transported via one or two airports, where they change the aircraft. When passengers do not fly non-stop, a discount on the price of the flight is given to compensate the discomfort. For a two-stop flight the discount is given two times. Passenger spill and recapture is not considered. Furthermore different aircraft types with their capacities and their fuel consumption are assigned to the flights.

As jet fuel costs become the major part of an airline's expenses and jet fuel prices have high fluctuations, this model explicitly considers the uncertainty of jet fuel prices with a scenarioset for each jet fuel price. The demand scenarios are also considered in a scenarioset and every demand scenario is combined with every fuel price scenario. The model is a two-stage stochastic program with $|no.\,of\,fuel\,scenarios| \times |no.\,of\,demand\,scenarios|$ scenarios.

To counteract jet fuel price uncertainty, this model considers financial hedging instruments. With forward-contracts/futures the purchases of jet fuel can be hedged. This model assumes that there are futures for jet fuel, which may not exist, but as Cobbs and Wolf (2004) argue, airlines can use futures on commodities whose prices highly correlate with jet fuel prices. The hedging can include a margin to model a risk premium or transaction costs and the amount of the jet fuel bought that can be hedged is arbitrary from 0 to 100 %. Reverse hedging or hedging more than 100 % is not allowed.

The jet fuel price scenarios and the prices for the financial instruments are adjusted to each other, so that there is no riskless arbitrage strategy.

As risk measure we use the CVaR. The value of the CVaR denotes the average value of a certain percentage of the worst scenarios. Usual percentages are 1, 5 or 10 %, for example. We use 10 % in the case study. Because it is a downside measure, it is a better risk measure than the often used variance that also increases with upside variations and should therefore only be used as risk measure in symmetric distributions. Compared to the Value at Risk, which denotes the threshold value between the x % worst scenarios and the other scenarios, the CVaR also considers the values of the x % worst scenarios and therefore fits very well to the perception of risk. It can be formulated as LP with the dual formulation of Fábián (2008). This formulation has been slightly adjusted and integrated.

Compared to literature, this is the first model that considers risk measures, financial hedging and jet fuel price uncertainty in one optimization model. Fuel price uncertainty and financial hedging have not been considered in one optimization model, yet. The model focuses on the demand und fuel price uncertainties, other uncertainties are not considered.

Altogether this model is a strategic optimization model for strategic airline planning under fuel price and demand uncertainty which considers risk/robustness measurement and financial instruments as countermeasures to uncertainty. Figure 4 shows the decisions and the corresponding data (in the blue boxes) of the optimization model.

3.2 The stochastic optimization model

Sets:

A	Set of airports
T	Set of aircraft types
FS	Scenarioset for jet fuel prices
DS	Scenarioset for demands

Parameters:

$dist_{i,j}$	Distance from airport i to airport j in km
$p_{i,j}$	Sell-price for a flight from i to j
$d_{i,j,ds}$	Flight demand from airport i to airport j (stochastic parameter)
pd	Price discount given for every aircraft change
x^{min}	Percentage of expected demand for every possible flight connection that has to be satisfied. Can ensure a certain service level
m_t	Passenger capacity of aircraft type t
$cons_t$	Jet fuel consumption of aircraft type t in liters per km
cpm_t	Operational cost per km of aircraft type t (without jet fuel costs)
$rmax_t$	Maximum range of aircraft type t
$rmin_t$	Minimum range of aircraft type t
ub_t	Maximum number of flightkilometers with aircraft type t
f_pr	Forwarded jet fuel price

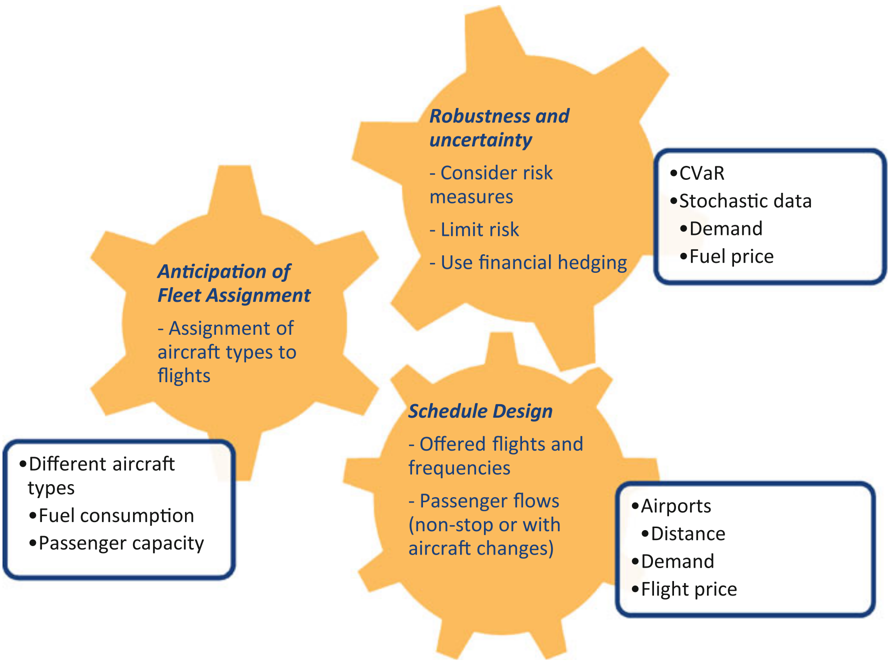


Fig. 4 Decisions and data in the optimization model

f_margin Margin for forwards in percent
pr_{fs} Jet fuel price per liter in fuel-scenario fs (stochastic parameter)
$prob_{fs,ds}$ Probability of demand scenario ds in jet fuel scenario fs
α Probability value for the CVaR

Stage-1-variables (fixed under uncertainty):

$y_{i,j,t;\forall i,j \in A:i<j}$ Number of flights per day from i to j and j to i with aircraft type t (non-negative integer variable)
buy_stoch Bought amount of fuel in liters to the stochastic price (nonnegative continuous variable)
buy_hedge Bought amount of fuel in liters to the hedged price (nonnegative continuous variable)

Stage-2-variables (independent for each scenario)

$x0_{i,j,ds\,i \neq j}$ Passenger flow—directly transported from i to j in demand-scenario ds (nonnegative continuous variable)
$x1_{i,k,j,ds\,i \neq j \neq k}$ Passenger flow—transported passengers from i to j over k with aircraft change on airport k in demand-scenario ds (nonnegative continuous variable)

$x2_{i,k,l,j,ds\,i\neq j\neq k\neq l}$	Passenger flow—transported passengers from i to j over k and l with aircraft change on airport k and airport l in demand-scenario ds (nonnegative continuous variable)

Accounting-variables:

$revenue_{ds}$	Revenue in demand scenario ds
$consumption$	Jet fuel consumption
$fuel\_costs_{fs}$	Jet fuel costs in fuel-price-scenario fs
$operationcosts$	Sum of operational costs (without jet fuel costs)
$profit_{fs,ds}$	Profit in demand scenario ds in jet fuel scenario fs
$cvar$	Conditional Value at Risk
$cvar\_y0$	Auxiliary variable for the dual CVaR-formulation
$cvar\_y_{fs,ds}$	Nonnegative auxiliary variables for the dual CVaR-formulation

Objective Function:

$$\max \sum_{fs\in FS, ds\in DS} prob_{fs,ds}\cdot profit_{fs,ds}$$

Constraints:

$$x0_{i,j,ds} + \sum_{k\in A: i\neq j\neq k} x1_{i,k,j,ds} + \sum_{k,l\in A: i\neq j\neq k\neq l} x2_{i,k,l,j,ds} \leq d_{i,j,ds} \quad \forall i,j\in A: i\neq j, ds\in DS \tag{1}$$

$$\begin{aligned} & x^{min}\cdot \sum_{ds\in DS}\sum_{fs\in FS} prob_{fs,ds}\cdot d_{i,j,ds} \\ & \leq \sum_{ds\in DS}\sum_{fs\in FS} prob_{fs,ds}\cdot \left(x0_{i,j,ds} + \sum_{k\in A: i\neq j\neq k}\left(x1_{i,k,j,ds} + \sum_{l\in A: i\neq j\neq k\neq l} x2_{i,k,l,j,ds}\right)\right) \\ & \forall i,j\in A: i\neq j \end{aligned} \tag{2}$$

$$\begin{aligned} & x0_{i,j,ds} + \sum_{k\in A: i\neq j\neq k}\left(x1_{i,j,k,ds} + x1_{k,i,j,ds}\right) + \sum_{k,l\in A: i\neq j\neq k\neq l}\left(x2_{i,j,k,l,ds} + x2_{k,i,j,l,ds} + x2_{k,l,i,j,ds}\right) \\ & \leq \sum_{t\in T} m_t\cdot y_{ijt} \quad \forall i,j\in A: i<j, ds\in DS \end{aligned} \tag{3}$$

$$\begin{aligned} & x0_{i,j,ds} + \sum_{k\in A: i\neq j\neq k}\left(x1_{i,j,k,ds} + x1_{k,i,j,ds}\right) + \sum_{k,l\in A: i\neq j\neq k\neq l}\left(x2_{i,j,k,l,ds} + x2_{k,i,j,l,ds} + x2_{k,l,i,j,ds}\right) \\ & \leq \sum_{t\in T} m_t\cdot y_{jit} \quad \forall i,j\in A: i>j, ds\in DS \end{aligned} \tag{4}$$

$$y_{ijt} = 0 \quad \forall i,j\in A: i<j, t\in T,\ if\ dist_{i,j} > rmax_t\ or\ dist_{i,j} < rmin_t \tag{5}$$

$$\sum_{i,j\in A: i<j}\sum 2\cdot y_{ijt}\cdot dist_{i,j} \leq ub_t \quad \forall t\in T \tag{6}$$

$$revenue_{ds} = \sum_{i,j \in A: i \neq j} p_{i,j} \cdot \left(x0_{i,j,ds} + (1 - \text{pd}) \cdot \sum_{k \in A::i \neq j \neq k} x1_{i,k,j,ds} + (1 - 2 \cdot \text{pd}) \sum_{k,l \in A: i \neq j \neq k \neq l} x2_{i,k,l,j,ds} \right) \quad \forall ds \in DS \tag{7}$$

$$consumption = \sum_{i,j \in A: i < j, t \in T} 2 \cdot y_{ijt} \cdot dist_{ij} \cdot cons_t \tag{8}$$

$$operationcosts = \sum_{i,j \in A: i < j, t \in T} 2 \cdot y_{ijt} \cdot dist_{ij} \cdot cpm_t \tag{9}$$

$$buy\_stoch + buy\_hedge = consumption \tag{10}$$

$$fuel\_costs_{fs} = buy\_stoch \cdot pr_{fs} + buy\_hedge \cdot f\_pr \cdot \left(1 + \frac{f\_margin}{100} \right) \quad \forall fs \in FS \tag{11}$$

$$profit_{fs,ds} = revenue_{ds} - fuel\_costs_{fs} - operationcosts \quad \forall fs \in FS, ds \in DS \tag{12}$$

$$cvar = \frac{-1}{\alpha} \left(\alpha \cdot cvar\_y0 + \sum_{ds \in DS, fs \in FS} cvar\_y_{fs,ds} \cdot prob_{fs,ds} \right) \tag{13}$$

$$cvar\_y0 + cvar\_y_{fs,ds} \geq - profit_{fs,ds} \quad \forall fs \in FS, ds \in DS \tag{14}$$

The objective function maximizes the expected profit, but the CVaR can also be maximized. The constraints (1) ensure that the passenger flow variables do not exceed the demand; minimum demand satisfaction is forced by (2). This should ensure a connection (with 0, 1 or 2 aircraft changes) between every pair of airports in the network, if there is a demand between these airports. The inequalities (3) and (4) implement aircraft capacity, (5) assures that the maximum and minimum distance of aircrafts is not exceeded. The constraints (6) ensure the maximum number of flightkilometers with an aircraft type while (7) assign the revenue. The constraints (8) calculate the consumed jet fuel and (9) calculates the additional operational costs. The equality (10) sets the variables for hedged and non-hedged fuel purchases. The fuel costs and the profit for every scenario are calculated in (11) and (12). Finally (13) and (14) integrate the CVaR into the optimization model.

The stage-2-variables are only indexed by the demand scenario and not by the fuel price scenario. This is possible, because when the flights are planned by the stage-1-variables the fuel-price does not have any impact on the transported passengers—as much as possible is transported for every demand scenario. Thereby we only need one tenth of the stage-2-variables, when we use 10 fuel price scenarios, and can decrease computational complexity. The connection of the fuel price scenarios and the demand scenarios is done by the accounting variables.

This two-stage stochastic program is solved as deterministic equivalent with a standard MIP-solver. The model is solved within a few minutes on a computer with Core2Duo 3.2 GHz, 8 Gb Ram and Windows 7 64 bit.

Table 1 Jet fuel price scenarios

Scenario	1	2	3	4	5	6	7	8	9	10
Jet fuel price $/l	0.06	0.11	0.17	0.28	0.41	0.55	0.69	0.83	1.05	1.38
Probability	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

3.3 An illustrative application

The data for this model is a small case study that was developed with a European airline. We consider two countries with 6 airports in each country; the countries are on different continents.

The considered aircraft types are a small one for domestic and medium-haul connections and a larger long-haul aircraft for intercontinental distances. The usage of aircraft types is constrained by a minimum range to avoid high consumption because of too short flights with large aircrafts and by their maximum range. The flight distance between the airports is always the shortest line between the airports.

To calculate the demand scenarios, we use the expected demand, which is symmetric for each pair of airports, for the flights and create a random value for each scenario from a normal distribution with $\mu =$ expected demand and $\sigma =$ expected demand/6 for each flight. These values are multiplied with factors from 77 % to 122 % depending on the 5 demand scenarios to create scenarios with different lower and higher total demands. Finally, negative values are set to 0. The value used for pd is 0.1; the value for α is also 0.1—therefore the worst 10 % of all scenarios are considered in the CVaR.

The jet fuel in November 2009 costs 0.55 $ per liter (see International Air Transport Association 2009a). The model takes 10 scenarios for the future jet fuel price into account. The spread of the fuel prices in the scenarios is quite large in order to examine the effects of the jet fuel price development (Table 1).

The fair forward rate for the scenarios is then calculated and an adjustable margin for the forward-contracts is added.

The parameter x^{min} is set to 0.5, which means that 50 % of the expected demand for each connection has to be satisfied. The prices of the flights depend on the combination of the countries of the origin and destination airport.

Note that in this example a new network is constructed. With this model, it would also be possible to refine an existing network, which is commonly done in practice. Then the y-Variables of non-modifiable flights should be fixed to the desired frequency of the connection between the two airports. This will also decrease the computational complexity of the model.

4 Results

4.1 Models for every jet fuel price scenario

The evaluation begins with a study of the impacts of different fuel prices on the optimal offered flights. We would like to show how they are determined by the

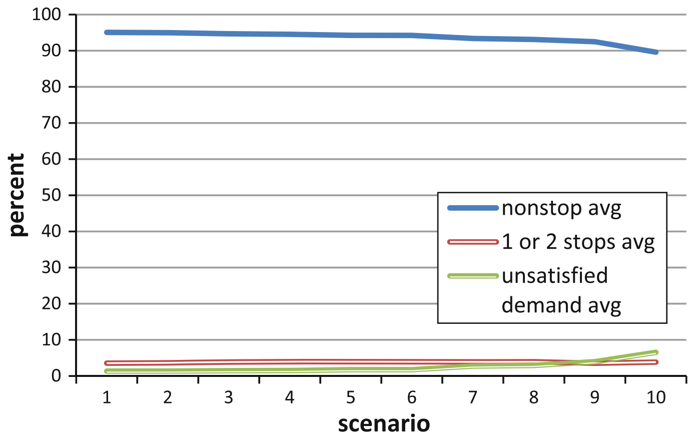


Fig. 5 Transported demand

development of the jet fuel price. Therefore, we optimize one model for each jet fuel price scenario without allowing financial instruments. The model for each jet fuel price scenario is also a stochastic model but the only uncertainty is the demand uncertainty. Then we look if the demand is satisfied and how many flights are carried out with each aircraft type. Figure 5 shows how many passengers are non-stop transported to their destination, how many are transported with an aircraft change and how many are not transported because their transportation would be unprofitable. (Note that the jet fuel price for scenario 1 is the lowest and for 10 the highest).

Figure 5 shows that if the jet fuel price rises, transporting fewer passengers becomes profitable and therefore more demand is not satisfied. The unsatisfied demand from scenario 1 to 5 is below 2 %, but grows to nearly 6.5 % in scenario 10. The percentage of non-stop transported passengers also decreases from 95 % in scenario 1 to 89.5 % in scenario 10, while the percentage of transported passengers with aircraft change is always between 3.5 and 4 %. This shows that the amount of flights with aircraft changes of all flights slightly grows with higher jet fuel prices, although those passengers are less profitable because of the discount that is given for aircraft changes and the additional fuel and operational costs that they cause because of the indirect route. Note that the percentages are the average percentages over the 5 demand scenarios for each jet fuel price scenario.

Figure 6 shows the average load factor of all flights depending on the different jet fuel prices. From scenario 1 to 4 values between 76 and 78 % are optimal. The optimal load factor grows to 84 % in scenarios 10, where the demand satisfaction decreases from >98 % in the scenarios 1 to 6 to 93 % in the highest fuel price scenario. The increase of the seat usage has a minor impact on the demand satisfaction in scenario 1 to 6. The impact becomes higher from scenario 7 on where the seat usage grows to values of 80 % and higher. The increase of the load factor now decreases the satisfied demand more significantly.

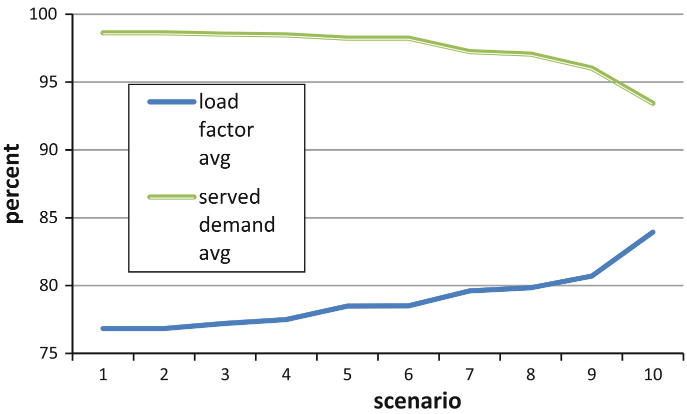


Fig. 6 Load factor

This may be explained by the demand uncertainty: When the average seat usage of all demand scenarios grows to higher levels higher than 80 %, we cannot transport all passengers in the higher demand scenarios. This additional demand in the higher demand scenarios is not satisfied, which causes the significant decrease in demand satisfaction. Connections also become unprofitable so that some flights are not offered anymore which decreases the demand satisfaction, too.

Financial hedging instruments are not considered in the models for every jet fuel price scenario, because as there is only one fuel price in each model and the profit is maximized for each scenario, the financial instruments could not change the risk.

Note that the results for this section, where one model for every fuel price scenario is created, might not be implemented without changes in practice. For example, the flight prices could be increased in the high fuel price scenarios so that more profitable flights could be offered, the demand satisfaction could increase, and lower load factors could be optimal because the aircraft does not need to have every seat occupied to be profitable. This section only shows the significant impacts of different fuel prices on offering the optimal flights by creating one solution for every fuel price scenario. In reality, one decision for offering flights has to be made here-and-now for all scenarios under fuel price uncertainty. This underlines the importance of considering fuel price uncertainty in the optimization model, what is done in the further results with the proposed model.

4.2 Models considering both uncertainties and robustness

In this section, we present the calculations for the stochastic model that considers all jet fuel price and demand scenarios. The decision which flights should be offered and flown has to be done under uncertainty. Also the amount of jet fuel that should be hedged is a stage-1-decision. The stage-2-decisions are the passenger flows. To measure robustness, we restrict the CVaR at different risk levels.

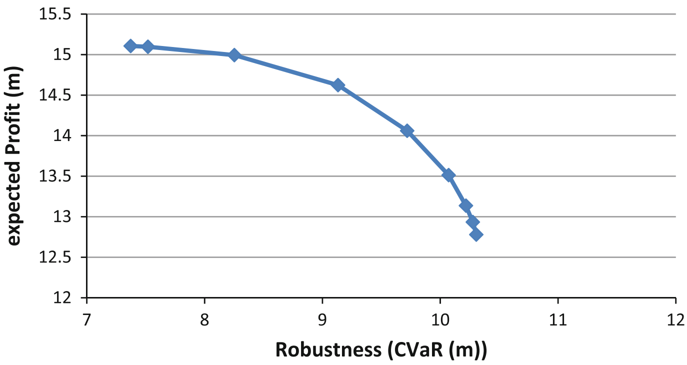


Fig. 7 Profit/risk-profile without hedging

4.2.1 Non-integrated hedging approaches

At first, we take a look at the risk/profit distribution of the model without financial instruments. Therefore, we first maximize the expected profit, then maximize the CVaR, and afterwards again the expected profit under the constraint of different risk levels. We first do this without financial instruments and obtain the pareto-frontline of optimal solutions shown in Fig. 7.

In Table 2, we compare the solutions with the highest expected profit (upper-left solution) and the lowest risk (bottom-right solution).

We can see that the most robust solution with the lowest risk has a CVaR of 10.306 m instead of 7.372 m. Also the profit in the worst scenario has increased from 5.522 to 9.296 m, and the spread between the best and the worst scenario is significantly lower. On the other hand, the expected profit has also decreased from 15.106 to 12.780 m. The risk is reduced by offering fewer flights and therefore consuming less jet fuel—the consumption is reduced by about one-third.

These significant changes show that gaining maximum robustness needs severe operational changes, which might not be desired in practice. One medium solution with CVaR 9.132 m, expected profit 14.623 m and 436 and 20 flights with the aircraft types might be the most robust and practical solution. Therefore, other methods for gaining robustness are necessary.

Table 2 Results highest expected profit—lowest risk

	Highest exp. profit	Lowest risk
Expected profit	15.106 m	12.780 m
CVaR	7.372 m	10.306 m
Profit of the worst scenario	5.522 m	9.296 m
Profit the best scenario	22.450 m	14.659 m
Scenarios with profit < -10 m	8	1
Flights medium-haul aircraft	502	330
Flights long-haul aircraft	26	16
Consumed jet fuel (l)	4.342 m	2.715 m

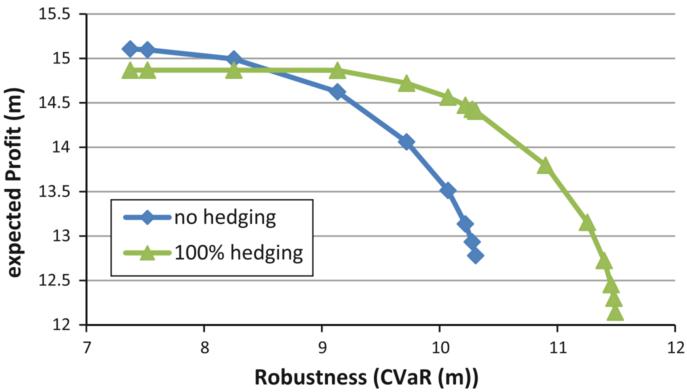


Fig. 8 Profit/risk-profile with 0 and 100 % hedging

An approach could be to hedge the bought jet fuel. We expect that the minimum risk exposure is obtained by hedging 100 % of the purchases. We then obtain the additional pareto-frontline in Fig. 8.

If the fuel purchases are completely hedged, the best CVaR can be increased significantly from 10.306 to 11.492 m. Hedging therefore can significantly increase robustness. But we also find out that the expected profit is lower than the maximum expected profit without hedging jet fuel. This is because the hedging premium lowers the expected profit. Hedging all jet fuel purchases is better than hedging no fuel purchases when the minimum accepted CVaR is higher than ~8.5 m (where the two lines cross each other).

We also see that the expected profit does not grow if we allow lower CVaR values than 9 m. Up to this CVaR, it is not necessary to change any flight or any passenger flow to gain less risk. The risk for the solutions with CVaR <9 m is completely covered by financial hedging. But could we gain more profit by hedging less jet fuel? Probably yes, because the costs for hedging premium then would also decrease. But which percentage of the bought jet fuel should then be hedged? And if we first create a flight schedule and then determine the amount of hedged jet fuel or vice versa, do we disregard interactions? These questions lead to the integrated consideration of financial hedging instruments in the next section.

4.2.2 Integrated hedging approach

This section shows the results for additional integration of financial hedging instruments into the optimization model. Now the amount of hedged fuel purchases is determined simultaneously with the other decisions in the model. This adds a degree of freedom and leads to this pareto-frontline in Fig. 9.

The first obvious result is that the integrated model has the best solution at all risk levels. This is because it can save the hedging premium in high-risk-solutions and is also able to determine the right amount of hedging in robust solutions in a way that not too much hedging (and thereby paying more hedging premium) lowers the expected profit. It therefore determines the best combination of hedging and

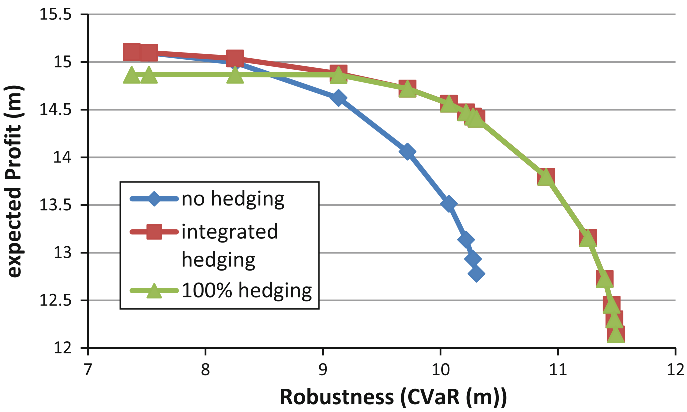


Fig. 9 Integrated profit/risk-profile

operational changes simultaneously to gain a certain risk level with the best possible profit.

In the case where the risk is minimized, we calculate the same solution in the integrated model and in the model where 100 % of the purchases are hedged; in the case where the profit is maximized with no other risk-constraints, the model without financial instruments and the integrated model create the same solution. In between, when a risk limit is specified, the solutions of the integrated model dominate the non-integrated approaches and always find the global optimum.

As nowadays fuel hedging is usually planned independently from operational planning in airlines' financial departments, and operational planning departments only take the percentage of hedged fuel into account, this can lead to worse solutions than the global optimum.

Furthermore, we look at a more detailed comparison of the different solutions with free and without hedging. Table 3 shows the expected profit, the number of flights with the different aircraft types and the amount of fuel hedged of the different solutions.

We can see that a significant decrease of flights in the solutions with hedging begin at higher robustness levels than in the solutions without hedging. The maximum robustness without hedging (CVaR = 10.31 m) can be gained by using hedging and a practically reasonable decrease of flights and profit. Very large changes in the number of flights offered are usually not desired, because usually only a small share of the aircraft used is chartered and only a few number of aircraft is separated out during a flight plan period.

We also spot that fuel hedging sometimes slightly decreases (from 99.8 to 99.6 % or from 100 to 99.8 %) although the CVaR is limited to higher values. These can be explained by interactions between financial and operational planning that the integrated model can utilize.

Because financial instruments can be integrated with a LP-based formulation, the computational complexity of the integrated model is not significantly increased. Therefore, we recommend using an integrated approach.

Table 3 Detailed results with and without hedging

Lower cvar limit (m)	Expected_profit (no hedging) (m)	Expected_profit (free hedging) (m)	Flights by medium aircraft (no hedging)	Flights by large aircraft (no hedging)	Flights by medium aircraft (free hedging)	Flights by large aircraft (free hedging)	% Fuel hedged (free hedging)
7.37	15.11	15.11	502	26	502	26	0
7.52	15.10	15.10	492	26	494	26	0.3
8.25	14.99	15.04	474	22	490	24	22.1
9.13	14.62	14.88	436	20	488	24	89.0
9.72	14.06	14.72	394	18	458	22	99.8
10.07	13.51	14.56	350	18	450	20	99.6
10.22	13.14	14.47	340	16	442	20	100
10.28	12.93	14.43	334	16	436	20	99.8
10.31	12.78	14.41	330	16	432	20	100
		13.80			388	18	100
		13.16			352	16	100
		12.73			326	16	100
		12.30			308	16	100

4.3 Evaluation of the stochastic model

To evaluate the model developed, we calculate two well known ratios for stochastic optimization models: The Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS). The EVPI is the difference between the here-and-now-solution and the wait-and-see solution of the stochastic model and therefore denotes the price that should be paid at maximum to purchase perfect information about the future. The Value of the Stochastic Solution (VSS) is the difference between the expectation of the expected value (EEV-Solution) and the here-and-now solution. To gain the EEV-solution, all uncertain parameters are set to their expected value, the optimal solution of a deterministic model with these parameters is calculated and evaluated for every scenario. The expected value of these solutions is the EEV. The VSS therefore denotes the advantage of solving a stochastic model instead of a deterministic model.

For this model maximizing the expected profit with both uncertainties and no hedging the EVPI is 1.195 m. If hedging is allowed the EVPI grows to 1.773 m. This is because hedging can gain additional profit, if the airline knew the future price of the jet fuel and can then hedge it only in the scenarios where the future price is higher than the fair hedge rate. This value is therefore hypothetical.

The VSS is 0.578 m in both cases. It does not change because there are no wait-and-see decisions like in the models that calculate the EVPI. This value underlines the benefit of using stochastic optimization models for this application.

5 Conclusion

This paper addresses strategic airline planning under jet fuel price uncertainty. A new stochastic optimization model that considers fuel price and demand uncertainty was developed. Furthermore, financial hedging instruments and a risk measure, the CVaR, was implemented to create the first optimization model for strategic airline planning considering financial hedging and operational planning integrated in one stochastic optimization model.

The results first examined the impacts of different jet fuel prices. It was shown that higher jet fuel prices make more flights become unprofitable. Passengers will have to accept more aircraft changes when jet fuel prices increase. Also less empty seats are optimal at higher fuel prices. It could be shown that different jet fuel prices have a high impact on optimal strategic airline planning.

Furthermore the developed model that considers jet fuel price and demand uncertainty was used to examine the robustness of the solutions by creating profit/risk-profiles for a model variation without hedging, for a variation with hedging 100 % purchases and for an integrated consideration. It has been shown that the integrated consideration gives better solutions because it allows interaction between financial instruments and the operational decisions. Financial instruments can significantly increase the robustness when risk is restricted.

In future research, more sophisticated models that include fuel price uncertainty, financial hedging and several planning steps like airline schedule design and airline fleet assignment could be developed. Aspects like several booking classes may also be included. To solve these proposed models with real data, more computational power and/or specialized solution algorithms is necessary.

References

Air France Press Office (2008) The air France commitment to the environment. http://corporate.airfrance.com/uploads/media/DP-Environnemental-EN.pdf. Accessed 01 June 2011

Air Transportation Association (2010) Annual traffic and ops: world airlines. http://www.airlines.org/economics/traffic/World+Airline+Traffic.htm. Accessed 10 Feb 2010

Air Transportation Association—Office of Economics (2009) U.S. passenger airline cost index—2nd quarter 2009. http://www.airlines.org/economics/finance/Cost+Index.htm. Accessed 17 Nov 2009

Barla P (1999) Demand uncertainty and airline network morphology with strategic interactions. Université Laval—Département d'économique—Cahiers de recherché No 9907

Barla P, Constantatos C (1999) The role of demand uncertainty in airline network structure. Université Laval—Département d'économique—Cahiers de recherché No 9903

Barnhart C, Cohn A (2004) Airline schedule planning: accomplishments and opportunities. Manuf Serv Oper Manag 6(1):3–22

Birge JR, Louveaux F (1997) Introduction to stochastic programming. Springer, New York

Carter DA, Rogers DA, Simkins BJ (2006) Does hedging affect firm value? Evidence from the US airline industry. Financ Manag 35(1):53–86

Cento A (2009) The airline industry. Springer, Heidelberg

Cobbs R, Wolf A (2004) Jet fuel hedging strategies: options available for airlines and a survey of industry practices. Finance 467

Deutsche Bank Research (2008) Aviation sector in crisis: there will be consolidation, but not a bloodbath. http://www.dbresearch.de/PROD/DBR_INTERNET_DE-PROD/PROD0000000000231327.pdf. Accessed 01 June 2011

Energy Information Administration (2009) Petroleum navigator. http://tonto.eia.doe.gov/dnav/pet/pet_pri_spt_s1_d.htm. Accessed 26 Nov 2009
Etschmeier MM, Mathaisel D (1985) Airline scheduling: an overview. Transp Sci 19(2):127–138
Fábián CI (2008) Handling CVaR objectives and constraints in two-stage stochastic models. Eur J Oper Res 191:888–911
Gopalan R, Talluri KT (1998) Mathematical models in airline schedule planning: a survey. Ann Oper Res 76:155–185
Hsu C, Wen Y (2000) Application of Grey theory and multi objective programming towards airline network design. Eur J Oper Res 127(1):44–68
Hsu C, Wen Y (2002) Reliability evaluation for airline network design in response to fluctuation in passenger demand. Omega 30(3):197–213
Hull JC (2003) Options, futures and other derivates, 5th edn. Prentice Hall, New Jersey
International Air Transport Association (2009a) Jet fuel price monitor. http://www.iata.org/whatwedo/economics/fuel_monitor/index.htm. Accessed 22 November 2009
International Air Transport Association (2009b) Load factors drop as passenger demand falls—freight stabilises. http://www.iata.org/pressroom/pr/2009-04-28-01.htm. Accessed 10 Feb 2010
Kall P, Wallace SW (1994) Stochastic programming. Wiley, Chichester
Lederer PJ, Nambimadom RS (1998) Airline network design. Oper Res 46(6):785–804
List GF, Wood B, Nozick LK, Turnquist MA, Jones DA, Kjeldgaard EA, Lawton CR (2003) Robust optimization for fleet planning under uncertainty. Transp Res Part E 39(3):209–227
Lohatepanont M, Barnhart C (2004) Airline schedule planning: integrated models and algorithms for schedule design and fleet assignment. Transp Sci 38(1):19–32
Sherali HD, Zhu X (2008) Two-stage fleet assignment model considering stochastic demands. Oper Res 56(2):383–399
Sherali HD, Bish EK, Zhu X (2006) Airline fleet assignment concepts, models, and algorithms. Eur J Oper Res 172(1):1–30
Soumis F, Ferland JA, Rousseau JM (1980) A model for large—scale aircraft routing and scheduling problems. Transp Res Part B 14:191–201
Triantis AJ (2005) Corporate risk management real options and financial hedging. In: Frenkel M, Hommel U, Rudolf M (eds) Risk management, 2nd edn. Springer, Berlin, pp 591–608
Wen Y, Hsu C (2006) Interactive multiobjective programming in airline network design for international airline code-share alliance. Eur J Oper Res 174(1):404–426
Yan S, Tang C, Fu T (2008) An airline scheduling model and solution algorithms under stochastic demands. Eur J Oper Res 190(1):22–39
Yu G (ed) (1998) Operations research in the airline industry. Kluwer, Boston