How to Approach New Industries and Gain Insights Into Their Development Dynamics
- Examples of the German Aviation Industry

Friederike Behrens
friederike.behrens@ecad-aviation.de

Eva-Maria Cronrath
eva.cronrath@ecad-aviation.de

Alexander Zock
alexander.zock@ecad-aviation.de

* European Center for Aviation Development - ECAD GmbH
Lise-Meitner-Straße 10
D-64293 Darmstadt
Phone +49 6151 3605 400
Fax +49 6151 3605 490

In today's business environment it is essential to be able to gain insights in a yet unfamiliar industry under tough time constraints. The 7 step framework we suggest addresses this issue. Following the standardised sequence of steps will direct the user to identifying the industry's main influencing factors. The historical development of the industry's output variable will be approximated by model simulations. An analysis of the peaks in relative deviations between real and simulated data will spotlight the industry's significant events and influencing factors. Compared to traditional market and environment analysis techniques our framework takes the particular industry's development dynamics into account. Thus we choose System Dynamics as underlying methodology which has already proven useful for understanding market dynamics and gaining structural insights. The 7 step framework will be illustrated with the development of passenger traffic at German airports.

Keywords: Industry Dynamics, Air Transport, Airports, Peak Travel

Today's business world consists of various industries in which we observe diverse developments. Therefore, decision makers such as politicians, managers, consultants, methodology specialists, or researchers can often find themselves confronted with the demand to gain insights in an industry they are not familiar with. The question is, how to approach an industry you cannot enlighten drawing from your experience. How can you achieve a general understanding of that industry given the usual tight time constraints? We aim to give a framework to address this issue using the civil air transport industry in Germany as an example.

The literature in the field of market and environment analysis is extensive though mostly building on a selection of traditional techniques (see e.g. Mintzberg, 2005; Homburg/Krohmer, 2003; Johnson/Scholes, 2002). Among those are Porter's (1979; 1980) five forces industry analysis and the strategic group analysis (Porter, 1980; Welge/Al-Laham, 2008) which aim to understand the situation within an industry. Besides approaches such as the SWOT analysis (Sudharshan, 1995; Chermack/Kasshanna, 2007) and the PEST(EL) framework (Johnson/Scholes, 2002) are intended to also include information about **p**olitical, **e**conomic, **s**ocial, **t**echnological, **e**nvironmental and **l**egal influences on an industry.

Using these traditional techniques when faced with the need to develop an understanding for a new industry promises a sound comprehension of the market, its mechanisms and the future opportunities and threats it yields. However, there are disadvantages attached to the traditional techniques. First, they require a large amount of data and moreover time investment. For a person without experience in the particular industry a compilation of the PESTEL factors, for example, is probably as time consuming as evaluating the threat of substitute products or the degree of competitive rivalry as forces in the yet unfamiliar market. In practise both time and data resources are usually scarce. Secondly, the traditional techniques are static. The analyses look at the market's present situation only and try to incorporate possible future scenarios based on foreseeable events. The market's development dynamics up to the present day are not taken into account.

The question is, given time and data constraints how can we ensure to capture the important facts concerning the new industry? How can we understand the industry's development dynamics? In this paper we suggest a framework for getting insights into new industries that (1) directs the user straight to significant events and influences and (2) accounts for the particular industry's dynamics. The framework is a 7 step approach as illustrated in Figure 1. The underlying methodology is System Dynamics as it allows parameter-based simulations and has already proven useful for understanding market development dynamics and gaining structural insights (see e.g. Lyneis, 2000).

Step	**What to do**
1	Define industry's output variable according to your interest
2	Observe general trend in the historical development of the industry's output variable
3	Reduce complexity by focussing on the main players
4	Approximate the industry's growth pattern
5	Analyse differences between modelled and historical behaviour of output variable
6	Iterative process: Insert learnings in the model and analyse variances
7	Recapture your insights

Figure 1: Illustration of the framework

Step 1: Define industry's output variable
The first step to understanding an industry is to define its output variables of interest. In our example of air transportation the output could be measured in terms of passengers and freight transported at German airports. However, in this paper we assume to have an interest in passenger traffic at airports only[1].

Step 2: Observe general development trend
The next step is to observe a general trend in the historical development of the industry's output variable. Following our example, the progress of passenger traffic in Germany is shown in Figure 2 (see German Federal Statistical Office, 1951-2007). The general pattern we can observe is a growth trend. The data shows a steady growth pattern with short-term periods of stagnation and a high concentration of passenger traffic onto the top 10 airports in Germany. The curve further on displays a tendency towards different growth regimes (50s and 60s, 70s, 1982 - today).

Step 3: Reduce complexity
Before starting to conduct an analysis we suggest to reduce complexity by focussing on the industry's main players and their contribution to the general development. For passenger traffic in Germany we find that the top 10 airports in 2006 accounted for 92% of total annual air passengers in Germany (see Figure 2). Thus, we will limit our further analysis to the manageable number of 10 airports.

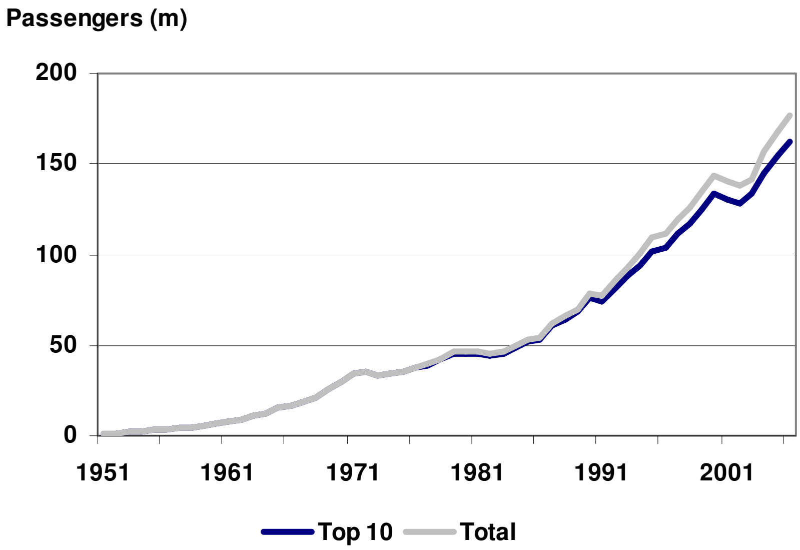

Figure 2: Passenger traffic at German airports in the years 1951-2006

Step 4: Approximate industry's growth pattern

To analyse the given growth data it was decided to employ a modelling approach that is not targeted at explaining the observed growth characteristics in detail, but tries to identify the

[1] Passenger traffic at airports is defined as the sum of passengers that have embarked or disembarked at all airports in a considered country.

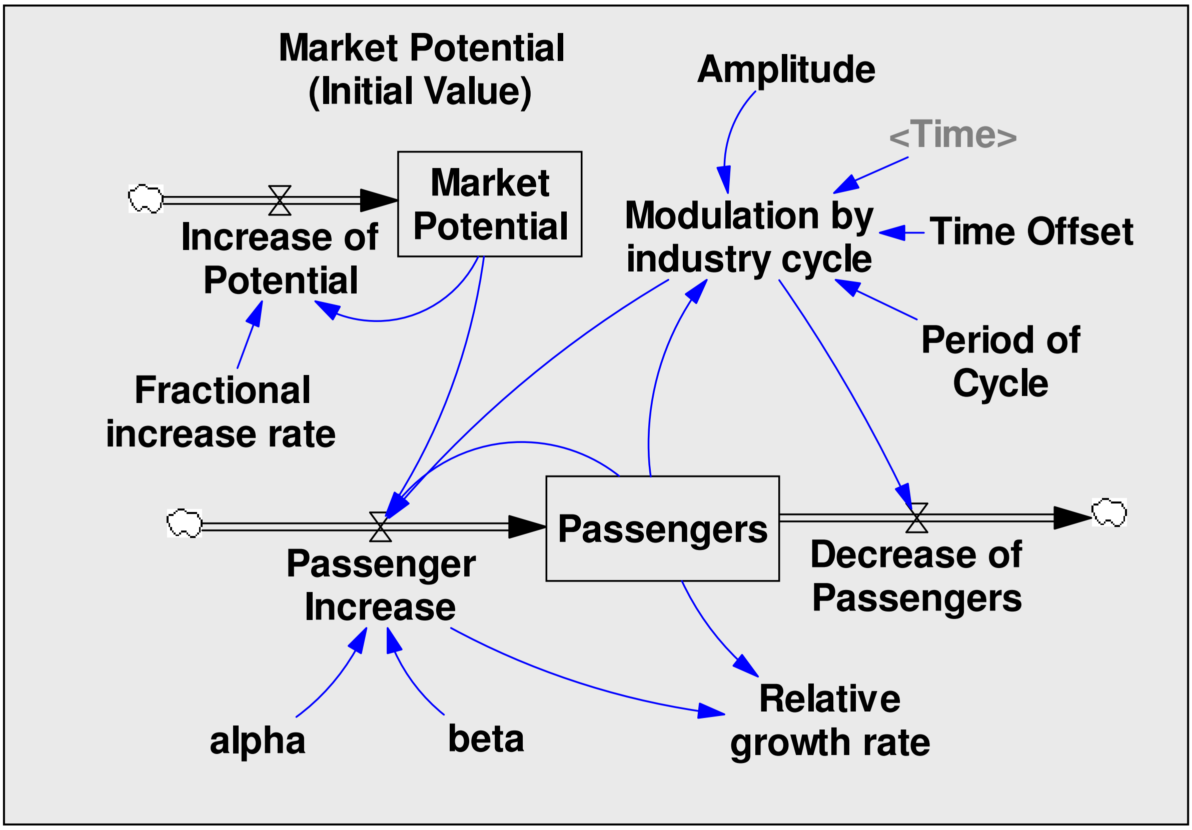

Figure 3: Logical Structure of the applied system dynamics model of an extended "Bass-model". In the framework of this paper, only the basic version of the "Bass-Model" was used.

archetypical growth pattern underlying the data. Typical patterns that can be observed in nature are for example linear, exponential, hyperbolic or logistic growth. Typically the first three growth patterns are only observed over a limited time period, whereas logistic growth might be applicable to quite longer time periods as its S-shaped growth characteristic reflects both growth driving as well as growth limiting processes.

A typical application of the logistic model can be found in the literature on product diffusion processes, e.g. the market penetration of a new electronic device in the market. The fundamental paper describing such application was published by Bass in 1969 (Bass, 1969). Bass incorporates in his model, which was consecutively also named "Bass-Model", the superposition of three processes: (a) a linear growth process proportional to a theoretical market potential for a product, which describes the starting phase of the logistic growth and might be identified for example with advertising efforts, (b) an exponential growth process that is proportional to the number of customers of the product under investigation (this part is often called the "word-of-mouth effect") and (c) a hyperbolic or super-exponential process that inhibits further growth and shows a square relationship to the number of customers divided by the market potential. According to Sterman (2000) and Mahajan/Muller/Bass (1990) the "Bass-Model" is the most widely used model to portray the diffusion of products.[2]

[2] Original notation (Bass 1969, 217): $f(t)/(1-F(t))=p+qF(t)=p+qY(t)/m$ with p and q as innovation and imitation coefficient, $F(t)$ as cumulative distribution function, and $f(t)$ as probability density function of the random variable t, the time of new product's adoption. $Y(t)$ as cumulative sales at time t, and m as total market potential.

A modified mathematical expression of the "Bass-Model" reflecting the above described structure looks as follows:

$$\frac{dA}{dt} = \alpha \cdot N + (\beta - \alpha) \cdot A - \beta \frac{A^2}{N}$$

with N being the market potential, A being the number of customers at a certain time and α and β being parameters that are normally used to describe the effectiveness of advertising and the "word-of-mouth" process. A depiction of the logical structure of the "Bass-Model" is shown in Figure 3, which additionally shows potential extensions of the simple model version in the form of inclusions of for example a variable potential market size or the variation of the customer growth rate by a cyclical process (e.g. business cycle).

To apply the "Bass-Model" to the considered growth process in the German Aviation system it is important to clarify the interpretation of the model structure in the framework of this industry setting. Here we assume that the product, whose diffusion is modelled by the "Bass-Model", is the use of air transportation. This means that a given number of customers at a certain moment in time will be interpreted not as identifiable individuals but simply as the number of flying people, whereas this number might include multiple purchases of a flight ticket by a certain individual as well as the exchange of customers in the course of time. Given this understanding of the model structure, the number of customers A does reflect the dynamic equilibrium number of passengers in the German Aviation system.

To apply the "Bass-Model" to the given data it is necessary to estimate the market potential for the considered market. This is a difficult task as there is no data available that can be relied on. Nevertheless, there are some data sources available that can be used to get an idea of the magnitude of the market potential e.g. the widely used traffic forecast by Intraplan (2006) for German airports. Intraplan estimates the market size for air travel in Germany in the year 2020 to be 307 million passengers. For the 10 biggest airports this number is expected to be about 270 million passengers. As no exact data was available for the theoretical market potential we used in the course of this work a rough estimation scheme in combination with a sensitivity analysis. Other approaches for market potential estimation can be found in the literature (see for discussion of methods e.g. Lee et al., 2007; Sakarya, 2006; Thomas, 1985).

The initialised "Bass-Model" is fitted to the historical data displayed in Figure 2 via an optimization routine that tries to minimise a so called pay-off-function that is a measure of the model prediction error[3].

When applied to the data, the analysis of the traffic at the top 10 airports in Germany shows a strikingly good agreement between model and passenger data as well as the data for

[3] The best fit between model curve and historical data is defined as having the maximum payoff. The payoff is a single number that summarises a simulation by which model parameters are compared to historical data. To find the maximum payoff, numerous simulations are run with varying diffusion parameters Alpha and Beta. The parameters are set to be equally important, so that their weights for the payoff calculation are 1. At each TIME STEP the historical data set is checked to see if a historical value is available. If it is available, the difference between the data and the model simulation is multiplied by the weight specified and this product is then squared. This number, which is always positive, is then subtracted from the payoff so that the payoff is always negative. Maximizing the payoff means getting it to be as close to zero as possible.

absolute growth and relative growth rates (the trend is captured over a period of 50 years) as can be seen from Figure 4 and will be discussed in more detail in the following.

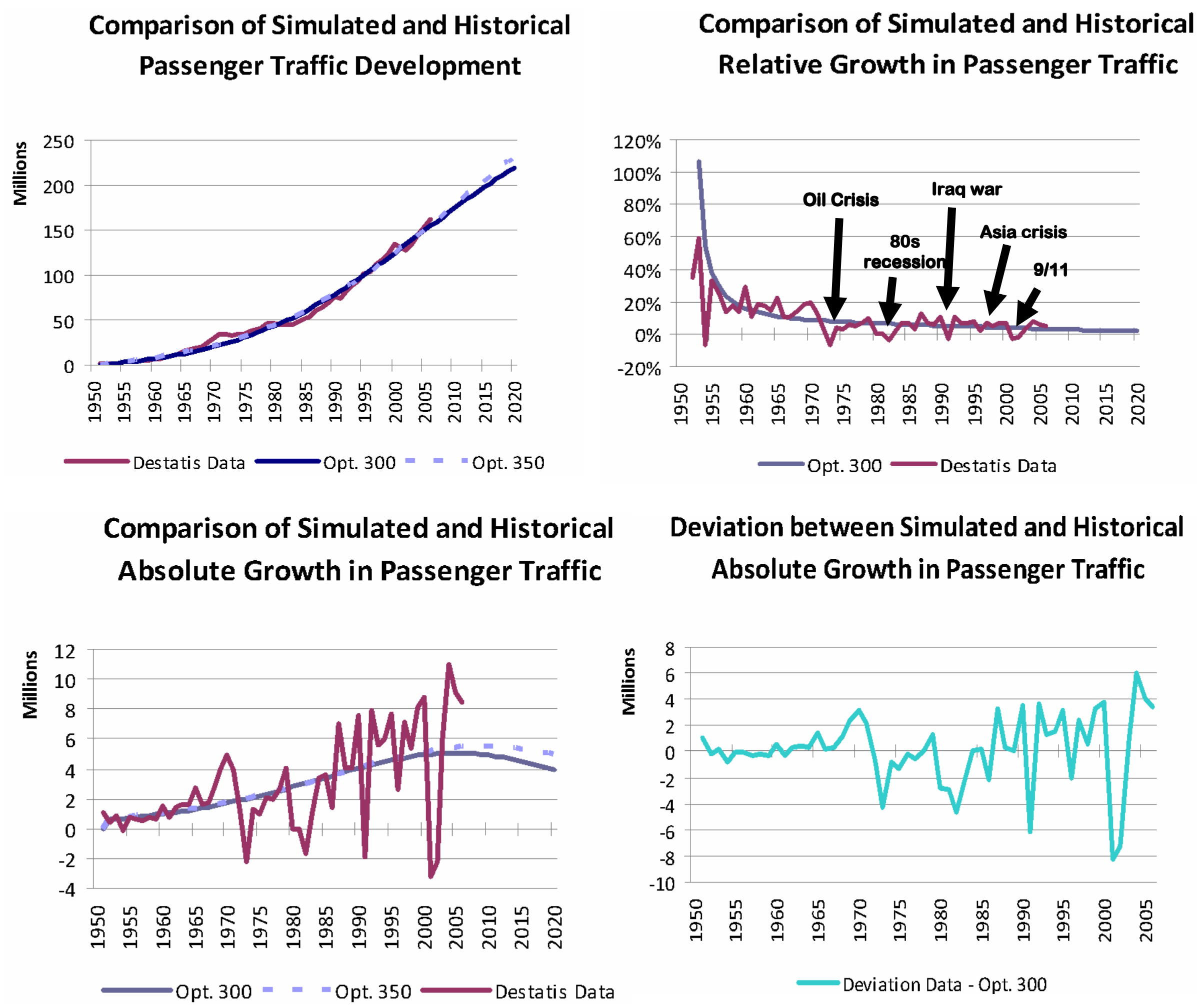

Figure 4: Approximating the growth pattern of passenger traffic at German Airports in the years 1951-2006 with an S-shaped growth pattern (based on a Bass-modelling approach): Historical data for passenger number versus model simulation (top left), historical relative growth rates versus predicted growth rate (top right), historical absolute growth rate versus predicted growth rate (lower left) and absolute deviation between absolute growth rate and predicted growth rate (lower right).

Step 5: Analyse differences between modelled and historical behaviour

(a) Comparison of the absolute number of passengers in the German Aviation system with the predicted number (Figure 4, top left):

From an overall perspective the agreement between historical passenger data and the predicted values is quite satisfying with an extremely good fit in the time period from 1950 to the end of the 1960s. In the 1970s a prominent deviation appears before the oil crisis in 1973, which might be attributable to the suppressed growth rates in the time after the oil crisis. For the period starting at about 1975 up to today it appears that the simulated curve reflects an average development that does not fit the historical data in detail, which seems to display a sequence of lower and higher growth rates if compared to the simulated curve. Nevertheless, through the succession of these varying growth rates, the average trend of the data is very well reflected in the simulated data as it was stated above. Interestingly, the influence of a variation of the theoretical market potential between 300 and 350 million passengers seems not to have a dramatic effect on the overall fit between the historical data and the simulation. A notable difference becomes only visible for the time period between 2010 and 2020.

(b) Comparison of the relative passenger growth rates in the German Aviation system with the predicted relative growth rates (Figure 4, top right):

If one considers the overall trend in the development of the relative growth rates for passengers in the German Aviation system it is interesting to note that the growth rates show a continuous decline over the last 50 years. This does not reflect a slow down in the growth dynamics (as can be seen from the discussion in the next section), but is merely the result of the fact that it is easier to grow at high rates when the base of the growth is smaller than when the base has grown to larger numbers. This phenomenon is often overlooked for example in the low cost discussion, where the higher growth rates of low cost carriers are often mistaken for higher absolute growth in passenger numbers when compared to classical carriers. Another interesting observation can be made if one concentrates on the dips in the historical data curve as these dips are clearly correlated to external factors as the first oil crisis (1973), the 80s recession, the second gulf war (1991), the Asia crisis (1997) and the events around 9/11. This correlation seems mainly to stem from the high correlation of industries growth to developments of the GDP (Helenius, 2003; Hamburg Airport, 2008; Pompl, 2006). Other influencing factors can be found in political events as for example in 1972 when the so called transit agreement between the Federal Republic of Germany and the former Soviet Union guaranteed landside access to West Berlin so that the airside connection between West Berlin and for example Hannover lost most of its importance and the overall growth rate of the top 10 airports in Germany declined sharply (see Treibel, 1992). All these events are clearly visible in the data and therefore show that the growth rates in the aviation industry are extremely sensitive to such events. Despite the fact that these dips are not reflected in the simple growth model that we applied here, it is encouraging to see that the overall average trend of the growth rates can be captured by the model quite nicely with deviations in both directions (under- and overestimation); an observation already described in the last section. Based on this finding a last interesting feature can be seen in the displayed curves, which is the continuous decline in growth rates predicted for the time period after 2008. According to the model the growth rates in the system will continue to decline up to the year 2020 and possibly onwards.

(c) Comparison of the absolute passenger growth rates in the German Aviation system with the predicted absolute growth rates (Figure 4, lower left and lower right):

The absolute growth rates for passengers in the German Aviation system show in their historic course an overall increase from the 1950s up to today. This overall growth trend is superimposed with strong deviations into the positive and the negative direction. If one compares these deviations with the external events described in the last section again a clear correlation is visible as can be expected. It appears that the logic behind these deviations is that an external crisis first hits the industry by suppressing the growth rates down to negative growth numbers to be followed then by growth numbers that exceed the average growth rates by far. This effect seems to reflect a tendency in the industry to catch up losses after a crisis by growth numbers that are higher than the average long-term numbers. This interpretation is further on corroborated by an analysis of the differences between the historical data and the simulated trend, as this data series shows mainly variations around the x-axis without any remaining clearly discernable trend.

If we summarise the findings described above it appears to be justified to put up the hypothesis that passenger growth in the German Aviation system can be characterised by a logistic-growth pattern. The deviation analysis further on spotlights the important influence which political, economic, social, technological, environmental and legal factors have had and will have on the growth pattern in the aviation industry. Based on these insights we will focus in the next step on possible further analysis and derivation discussions that can be performed on the basis of the above outlined hypothesis.

Step 6: Iterative process: Insert learnings in the model and analyse variances

In this step we will extend our analysis of the passenger data in the German aviation system in two ways. First, we will use the logistic growth hypothesis to derive some non apparent consequences for the aviation system if the system actually follows a logistic growth trajectory. Secondly, we will have a closer look at the observed deviations between the historical data and the simulated data to apply a time wise segmented growth simulation.

(a) "Peak Travel" analysis in the German aviation system:
A major drawback of the "Bass-Model" used in the last section has been its dependence on the beforehand knowledge of a theoretical market potential of a considered market. As such data is usually not available a detailed analysis of such a market is severely hampered. Fortunately it is possible to find in the literature a wealth of applications of the logistic-growth model to real world data sets that try to deal with this problem. An especially interesting application can be found under the term "Peak Oil" (see for example Hubbert, 1956; Deffeyes, 2001). The term "Peak Oil" relates to the phenomenon that the production rate of oil is expected to peak long before the available resources of oil will be depleted. This finding was first presented by M. King Hubbert in 1956 when he predicted that the US oil production would peak in the early 1970s, what it ultimately did. Hubbert's methodology mainly comprised the use of the hypothesis, that the production of crude oil follows a logistic growth pattern. Based on this assumption he derived from the mathematical formulation of logistic growth an approximation that allows deriving from empirical data on crude oil production the most likely point in time when "Peak Oil" will appear. This is done in a two step process which first includes the empirical derivation of an estimate for the overall size of the available oil resources and then based on that estimate the calculation of the "Peak Oil" point based on the relationship that "Peak Oil" appears for logistic growth patterns at the point in time, when half of the available resources of oil have been conveyed. In practice this two-step procedure is based on a graph that relates the amount of conveyed oil on the x-axis with the ratio of actual production divided by the cumulative amount of oil that has already been conveyed. If one plots empirical data about oil production in this graphs one gets for the long-term tail of the curve a straight line that intersects the x-axis at exactly the point where the available resources have been depleted completely, i.e. the theoretical size of the available resources.

The above explained scheme of "Peak Travel"-analysis can be applied to the aviation industry in the following way. The cumulative amount of conveyed oil is equivalent to the number of passengers one finds in the system at a certain point in time. This interpretation means that at zero growth we will not have zero passengers in the system but will find an equilibrium number of passengers that will continuously travel in the system. The ratio of the actual oil production to the cumulative amount of conveyed oil can be translated to the relative growth rate of passengers in the aviation system. Applying this translation scheme to the data of the German aviation system yields to the results displayed in Figure 5.

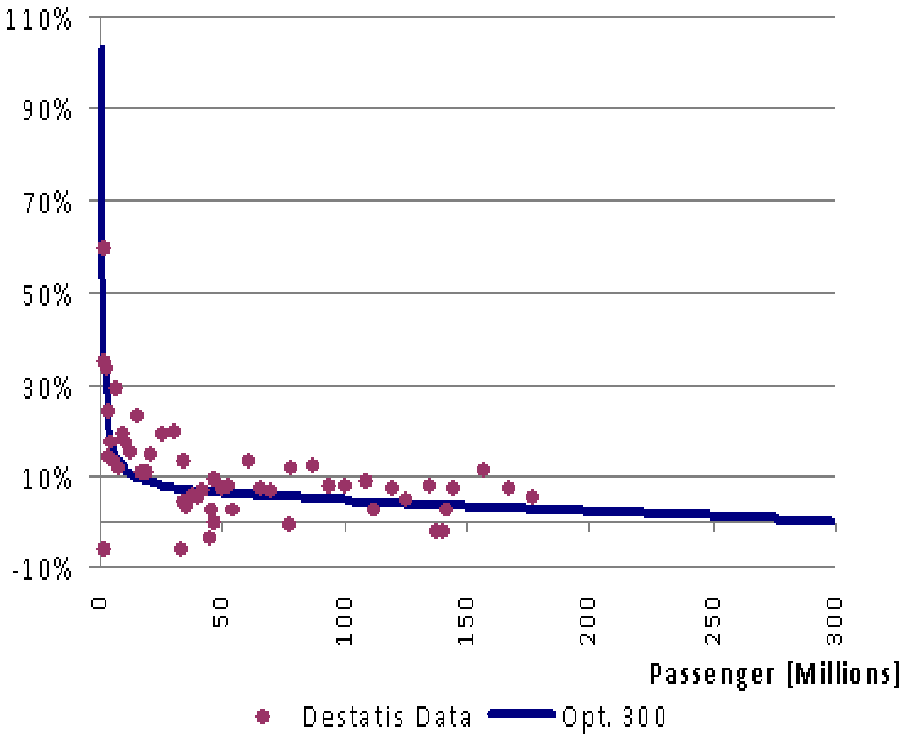

Figure 5: Comparison of a "Peak Travel" analysis for the German Aviation System based on the historic data displayed in Figure 4 in comparison to a simulated system growth trend using a "Bass-model"-simulation with a theoretical market potential of 300 million passengers.

Looking at the data displayed in Figure 5 the visible match between the simulated growth trend of the "Bass model" (assuming a market potential of 300 million passengers) and the historic data is again quite well. Additionally, it is interesting to note that the travel data, despite its noisy appearance, settles into a trend line as it would be expected based on the "Peak Oil" observations. Given this finding it appears to be possible that the German aviation system is heading for a "Peak Travel" point in the near future. If we assume market potentials of about 300 or 350 million passengers, this would even translate into "Peak Travel" points at around 2005 or 2007/2008. This result is also shown in Figure 4 (bottom left) in the simulated data for the absolute growth numbers in the German aviation system as these growth numbers clearly peak at the above stated points in time. Such findings are of great interest if we aim at understanding the future growth trajectory of the aviation industry in Germany, as a "Peak Travel" phenomenon would put highly challenging constraints on growth strategies of airlines operating in such an environment. Therefore, it is important to note that despite the apparent fit of the logistic growth model to the industry trend of the last 50 years, the mathematical consequences of such a similarity have so far not acknowledged. For example the possible existence of a "Peak Travel" phenomenon in the German aviation system, that might possibly appear in the near future, is not yet subject of discussions.

(b) Segmented growth modelling for the German aviation system:
In Step 5 in the course of the comparison of the historical data with the simulated data it was found, that the simulated curve showed an extremely good fit to the empirical data in the 1950s and the 1960s. After that time the growth characteristic seemed to have changed slightly so that as a consequence of this behaviour the fit in later years showed some higher deviations from the historic curve. Based on these observations it appears promising to compare the optimisation results that one would get if the analysis would be restricted to defined periods of time, e.g. 1951 – 1971 and 1982- today. The results of such a calculation are displayed in Figure 6. They show a strong deviation in the growth trend between both curves, with much higher growth rates for the curve that was fitted to the time period from 1951 – 1971. According to this growth scenario, the 2006 passenger number in the German aviation system would already have been reached at the end of the 1980s. Given these results it seems that the growth pattern in the industry went through a huge change during the early 1970s until it settled again for a weaker overall growth from the 1980s onwards.

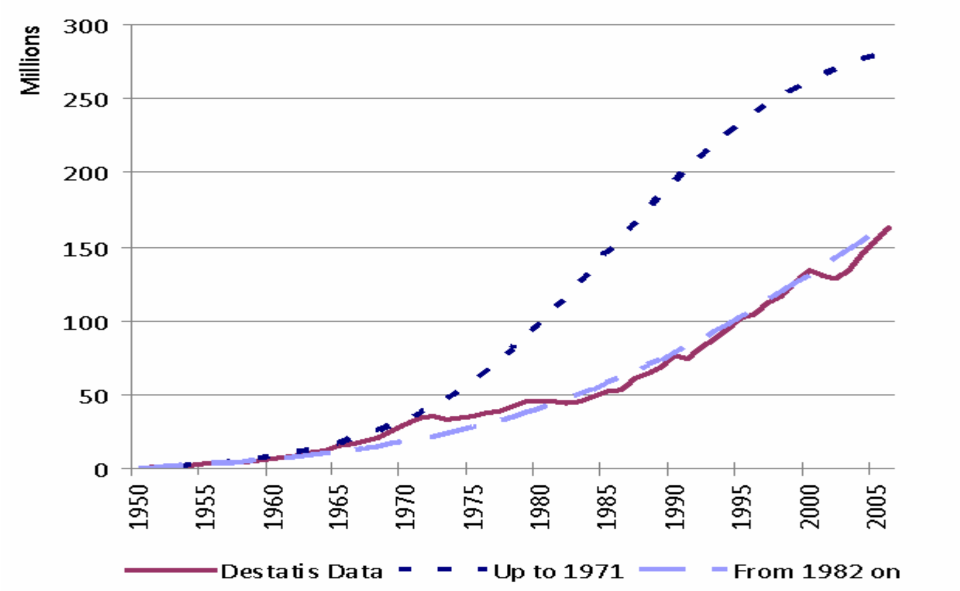

Figure 6: Historical development vs. segmented simulation model of passenger traffic at German airports for the time periods of 1951 – 1971 and 1982 onwards

If this segmentation approach is extended further to decrease the remaining deviations between the empirical data and the simulated data, we settle with a model that uses four segments between 1951 and 2006 that look as follows:

Segment 1: 1951-1972
Segment 2: 1973-1981
Segment 3: 1982-2001
Segment 4: 2002-2006

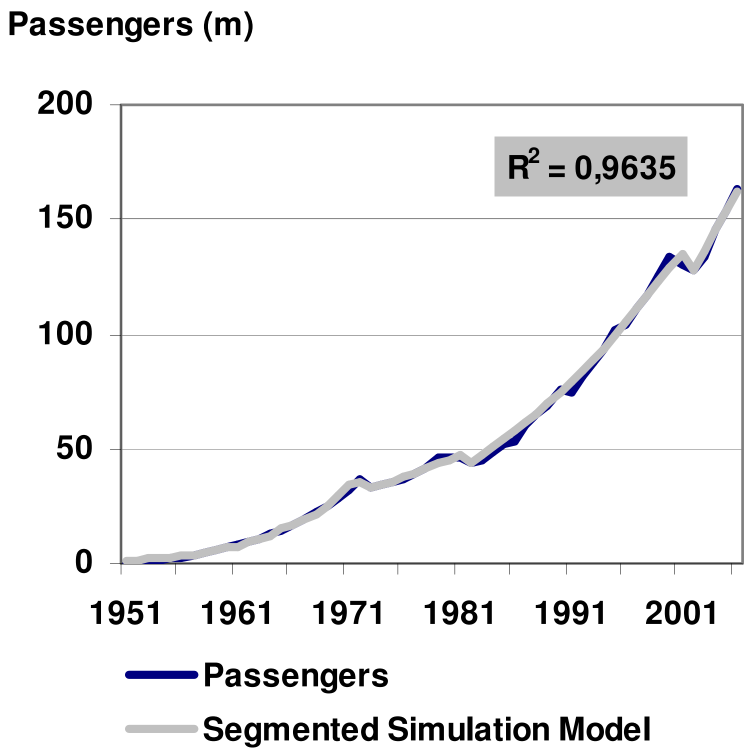

Figure 7: Historical development vs. extended segmented simulation model of passenger traffic at German airports in the years 1951-2006

Using this segmented model, an even better fit between the empirical and the simulated data can be achieved as can be seen in Figure 7. The four-segment model delivers an R^2 of 0.96, which reflects a high correspondence between the empirical data and the simulation data.

Step 7: Recapture your findings

Summarising the findings of the six steps that have been employed in the frame of this paper, it can be stated that the proposed analysis scheme is capable of aiding a thorough analysis of a key performance indicator of a complex industry like the aviation industry in a way that enables the identification of significant insights. The basic insights into the German aviation industry are:

- The growth pattern of the passenger number in the German aviation system can be approximated for the time period of the last 50 years by a logistic growth model ("Bass model").
- The logistic growth model does not only suitably characterise the overall growth trend in the passenger numbers of the German aviation system but is also capable of providing a good fit to the absolute and relative growth numbers per year.
- Major deviations between the model and the given empirical data are always related to external socio-economic or political influencing factors such as oil crises or economic recessions.
- The application of a "Peak Travel" analysis on the German aviation system, i.e. the assumption of a logistic growth pattern for passenger growth, enables the derivation of further unexpected insights into the industry.

- An extension of the simple modelling approach by a segmentation approach in time is capable of increasing the quality of the fit between the model output and the empirical data significantly.

Conclusions

The presented framework shall be understood as a complementary approach to various business techniques for examining an industry, tailored to todays usually time constrained situations. As opposed to many traditional techniques the framework focuses on gaining dynamic insights into the respective industry by basing the analysis on time series modelling. To conduct the analysis it is thus inevitable to have access to time series data on the desired industry output.

When contemplating emerging markets, however, a lack of historical data and possibly also difficulties in estimating a market potential will limit the frameworks applicability. Sakarya et al. (2007) discuss the specifics of dealing with emerging markets and also give examples of how to assess the market potential in such cases.

The framework is open to the users' own ideas in terms of which generic growth pattern to test for and how to insert learnings into the simulation model. To build on the "Bass model" and then extend this approach to a "Peak Travel" analysis or a segmentation approach is only one option. Another option could be to consider the influence of a business cycle in the model (see e.g. Liehr et al., 2001; Jiang/Hansman, 2006).

In today's business environment the demand to gain insights into a yet unfamiliar industry under tough time constraints is increasingly high. Although the literature in the field of market and environment analysis is extensive, the application of most traditional techniques involves some disadvantages, especially under time and data constraints. The 7 step framework we suggest addresses this issue.

Opposed to traditional techniques our framework puts its main focus on the particular industry development dynamics and is thus very similar to the standard System Dynamics modelling approach for dynamic problems (see for example Sterman, 2000).

By following a standardised sequence of steps the user will be able to identify the industry's main influencing factors. The historical development of the industry's output variable will be approximated by model simulations. A deviation analysis can then also reveal peak deviations between the historical and simulated values and will thus draw the user's attention to important industry specific turning points. Interpreting the spotlighted events will enable the user to improve the model and hence the approximation of the historical data. In addition the use of a model might extend ones analysis capability by a modest forecasting possibility.

Future research could focus on integrating a business cycle into the model as well as time-varying market potentials that would allow for an alternative incorporation of different stages in the industry's development. Lastly, it may also be worthwhile to replace the employed "Bass Model" by an industry adjusted modelling approach that would allow a more meaningful interpretation of used model parameters.

REFERENCES

Bass, F. M. 1969. A New Product Growth for Model Consumer Durables. *Management Science* **15(5)**: 215-227.

Chermack, T.J. and B.K. Kasshanna 2007. The Use and Misuse of SWOT Analysis and Implications for HRD Professionals. *Human Resource Development International* **10(4)**: 383-399.

Deffeyes, K. S. 2001. Hubbert's Peak. Princeton. NJ: Princeton University Press.

German Federal Statistical Office (Statistisches Bundesamt) 1952-2007. *Fachserie 8, Reihe 6.2: Verkehr – Luftverkehr auf ausgewählten Flugplätzen*, Wiesbaden: Statistisches Bundesamt.

Helenius, A. 2003. *Die ökonomische Entwicklung des Luftverkehrs im Lichte der Theorie der Kontratieff Wellen*. Göttingen: Cuvillier.

Homburg, Ch. and H. Krohmer 2003. *Marketingmanagement*. Wiesbaden: Gabler.

Hubbert, M. K. 1956. Nuclear energy and Fossil Fuels. American Petroleum Institute Drilling and Production Practice, Proceedings of the Spring Meeting, San Antonio, 1956, pp. 7-25.

Intraplan Consult GmbH im Auftrag der Initiative „Luftverkehr für Deutschland" 2006. *Luftverkehrsprognose Deutschland 2020 als Grundlage für den "Masterplan zur Entwicklung der Flughafeninfrastruktur zur Stärkung des Luftverkehrsstandortes Deutschland im internationalen Wettbewerb"*. München: Intraplan Consult GmbH.

Jiang, H. and R. J. Hansman 2006. An Analysis of Profit Cycles in the Airline Industry, *Proceedings of the 6th AIAA Aviation Technology, Integration and Operations Conference (ATIO).*

Johnson G. and K. Scholes 2002. *Exploring Corporate Strategy*. London: Financial Times Prentice Hall.

Lee, W. Y., P. Goodwin, R. Fildes, K. Nikolopoulos and M. Lawrence 2007. Providing Support for the Use of Analogies in Demand Forecasting Tasks. *International Journal of Forecasting* **23(3)**: 377-390.

Liehr, M., A. Größler, M. Klein and P. Milling 2001. Cycles in the Sky: Understanding and Managing Business Cycles in the Airline Market. *System Dynamics Review* **17(4)**: 311-332.

Lyneis, J.M. 2000. System Dynamics for Market Forecasting and Structural Analysis, *System Dynamics Review* **16(1)**: 3–25.

Mahajan, V., E. Muller and F. M. Bass 1990. New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing* **54**: 1-26.

Mintzberg, H., B. Ahlstrand, J. Lampel 2005. *Strategy Safari: A Guided Tour Through the Wilds of Strategic Management*. New York: Free Press.

Pompl, W. 2006. *Luftverkehr – Eine ökonomische und politische Einführung*. Berlin/Heidelberg: Springer.

Porter, M. E. 1979. How Competitive Forces Shape Strategy. *Harvard Business Review* **57(2)** March-April: 137-145.

Porter, M. E. 1980. *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Sakarya, S. 2007. Market Selection for International Expansion Assessing opportunities in Emerging Markets. *International Marketing Review* **24(2)**: 208-238.

Sterman, J. D. 2000. *Business Dynamics - Systems Thinking and Modeling for a Complex World*. Boston: McGraw-Hill.

Sudharshan, D. 1995. *Marketing Strategy*. Englewood Cliffs: Prentice Hall.

Thomas, R. J. 1985. Estimating Market Growth for New Products: An Analogical Diffusion Model Approach. *Journal of Product Innovation Management* **2**: 45-55.

Treibel, W. 1992: Geschichte der deutschen Verkehrsflughäfen, Bonn: Bernhard & Graefe.

Welge, M.K. and A. Al-Laham 2008. Strategisches Management: Grundlagen – Prozess – Implementierung, Wiesbaden: Gabler.

Online Sources

Hamburg Airport. *Historie*. http://www.flughafen-hamburg.de/de/historie_812.htm. Date of access: 19 Mar 2008