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An Analysis of Profit Cycles in the Airline Industry

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[Abstract] This paper discusses the financial dynamics of the airline industry by identifying the fundamental cycle periods of profitability and their driving factors. Assuming the industry profit cycles could be modeled as an undamped second-order system, the fundamental cycle period was found to be 11.3 years for the U.S. airline industry and 10.5 years for the world airline industry. An empirical profitability model was estimated and the results revealed that such cycle period is endogenous, neither deregulation nor September 11 have significantly changed the cycle length. To analyze the causes of profit cyclicality, parametric models were developed under the hypothesis that phase lag in the system caused the profit oscillations; and two hypotheses, lag in capacity response and lag in cost adjustment were studied. Analysis of the parametric model of capacity response indicated that the system stability depends on the delay between aircraft orders and deliveries and on the aggressiveness in airplane ordering. Exaggerated capacity response was observed in the simulation as the gain in the model has lumped impacts of exogenous factors, suggesting capacity shortfall alone cannot fully explain the industry dynamics. The model also indicates reducing delay may help to mitigate system oscillations. Simulation results of the parametric model regarding cost adjustment were consistent with profit observations. Finally, a coupled model was developed to study the joint effects of capacity and cost. Simulation results indicated that the coupled model explained industry dynamics better than individual capacity or cost models, suggesting that the system behavior is driven by the joint effects of capacity response and cost adjustment.

Nomenclature

T	=	fundamental cycle period of the profitability of the airline industry
τ	=	e-folding time indicating how rapidly the amplitude grows
t	=	time
t_0	=	time instant the system crosses zero
A	=	amplitude of profit oscillation
$x(t)$	=	industry profit or loss in billions of constant 2000 dollars
C_0	=	intercept
K	=	control gain in the capacity/cost parametric model
D	=	delay in the capacity/cost parametric model
ω_{crit}	=	critical frequency at which the system oscillates with constant amplitude
T_{crit}	=	critical cycle period corresponding to ω_{crit}
K_{crit}	=	critical gain corresponding to ω_{crit}

I. Introduction

THE air transportation in the United States has experienced rapid development through boom-and-bust cycles, particularly since deregulation in 1978. Prior to 1978, the airline industry resembled a public utility; the routes each airline flew and the fares they charged were regulated by the Civil Aeronautics Board (CAB)[1]. As the Airline Deregulation Act eliminated CAB's authority over routes and domestic fares, the airline industry transformed into a market-oriented sector, driven by the dynamics between demand and supply.

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Deregulation has promoted the development of air transportation system; as shown in Fig. 1 the rapid growth in traffic and operating capacity, measured by Revenue Passenger Miles (RPM) and Available Seat Miles (ASM) respectively[2]. The annual growth of domestic scheduled traffic of the U.S. airlines between 1978 and 2002 averaged 11.7 million RPMs per year, more than doubled the average growth between 1954 and 1978 that was 5.8 million RPMs per year[3], and the operating capacity of the industry grew on average 4% per year between 1980 and 2000.

Despite the rapid growth, the net financial results of the industry exhibited a significantly different behavior. The annual operating revenues and expenses[4] of the U.S. major, national and regional passenger and cargo airlines have grown with traffic (Fig. 2), whereas the industry profits[4] (Fig. 3) have oscillated around zero with growing amplitude, suggesting that fundamental changes took place in the industry since deregulation. In recent down cycle, the industry has lost over 23 billion dollars accumulatively in 2001, 2002 and 2003, outpacing the total earnings of the past. Many airlines have suffered intense financial losses. In past five years, major airlines, such as United Airlines, US Airways, ATA Airlines, Northwest Airlines, and Delta Air Lines, have filed bankruptcy protection. By contrast, the industry was profitable most of the time before deregulation even in the down cycles (Fig. 3). It should be noted that data in Fig. 2 and Fig. 3 were evaluated in constant 2000 dollars to eliminate the inflation effects. Unless otherwise noted, all financial data in this study is referred to 2000 dollars.

The above observation of growing profit oscillations after deregulation could not be simply explained by traffic or capacity growth. Shown in Fig. 4 are the unit profits of the industry since deregulation. The unit profit was derived from normalizing the net profit with respect to ASM of the year to eliminate the effect of capacity increase on profit growth. Again, the amplitude of oscillating unit profits has grown over the cycles since deregulation.

Moreover, similar observation is also seen in the world airline industry. As the wave of liberalizing air transportation spreads globally, the world air traffic and capacity have grown rapidly since the late 1970s. Shown in Fig. 5 are the annual traffic (RPK) and operating capacity (ASK) of the world airlines recorded by ICAO[5]. The annual growth rate of capacity averaged 4.7% during the 1980s and 1990s. On the other hand, the net profits of the

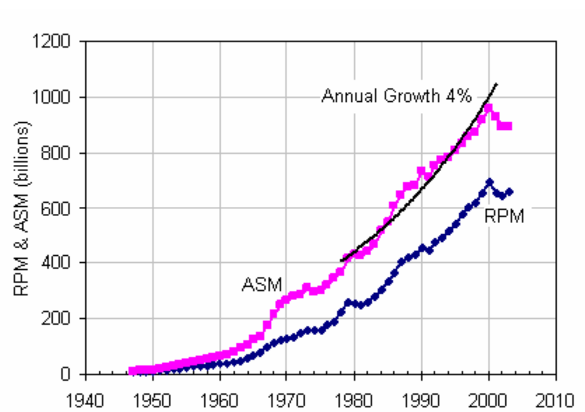

Figure 1. Annual Traffic and Capacity of Scheduled Services of the U.S. Airline Industry[2].

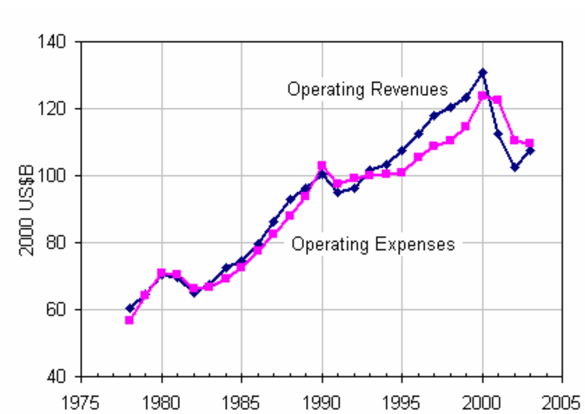

Figure 2. Annual Operating Revenues and Expenses of All Services of the U.S. Airline Industry[4].

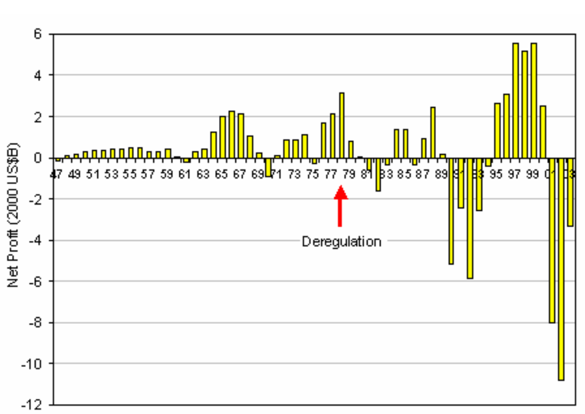

Figure 3. Annual Net Profits of All Services of the U.S. Airline Industry[4].

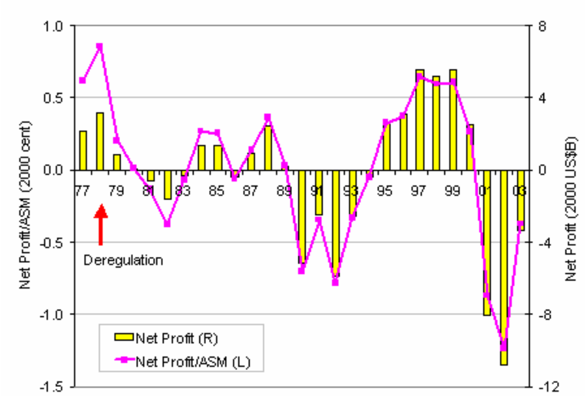

Figure 4. Unit Net Profits of the U.S. Airline Industry.

world airlines again have oscillated with increasing amplitude over the years since the late 1970s (Fig. 6)[5].

Although the cyclical behavior of the airline industry has been widely noticed by industry professionals and external financial investors, majority of the researches focused on the dynamics between orders and deliveries of commercial jets[6, 7], with little on the fundamental cycle period of industry profitability and its causes. The financial crisis facing the U.S. airlines in 2001-2003 has highlighted the volatility and oscillation of industry profits as a key issue for the stability of airline industry. The objective of this study is to understand the dynamics of airline industry by identifying the fundamental cycle periods of industry profitability as well as the driving factors.

The study took a system approach to analyze the profitability of airline industry. Assuming the oscillating profits resemble an undamped second-order system, a spectrum analysis was conducted to identify the fundamental cycle periods, followed by the estimation of empirical profitability models of the U.S. and world airline industries. To explore the causes of profit cyclicality, parametric models were developed under the hypothesis that phase lag in the system causes profit oscillations; and two hypotheses, lag in capacity response and lag in cost adjustment were examined first separately and later jointly. A root locus analysis was performed to explain the system stability and simulations were executed to verify the hypotheses. Last, a coupled model was developed to assess the joint effects of capacity response and cost adjustment.

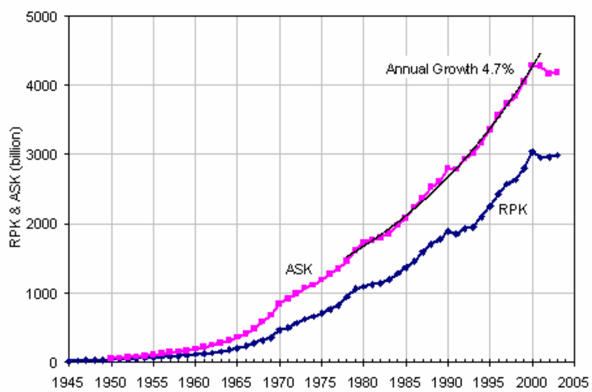

Figure 5. Annual Traffic and Capacity of the World Airline Industry[5].

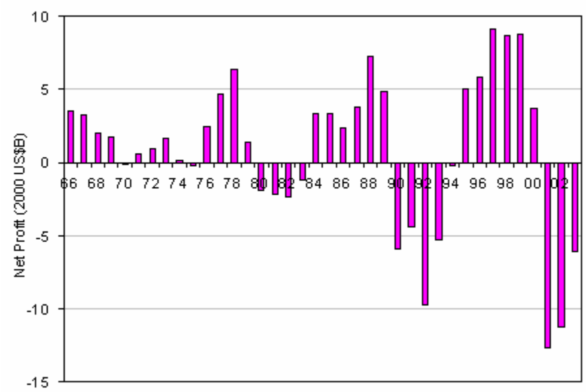

Figure 6. Annual Net Profits of the World Airline Industry[5].

II. Fundamental Cycle Periods and Empirical Models of the Profitability of Airline Industries

A. Fundamental Cycle Periods of the Profitability of Airline Industries

Signal detection approach was used to identify the fundamental cycle period T of the profitability of airline industry. Viewing historical profit data of airline industry as a set of noisy signals containing information about the system characteristics, Discrete Fourier transform (DFT) was applied to the profit data to identify the fundamental frequency of the system. Detailed discussion of DFT analysis can be found in Ref. 8 on pages 24-25.

Annual profit data of the U.S. airlines between 1980 and 2002 were analyzed, and the fundamental frequency of the profitability of the U.S. airline industry was found to be 0.0938/year (Fig. 7). Seen in the figure, the magnitude of the fundamental frequency is about 6dB higher than that of the second frequency, meaning that the magnitude of the fundamental frequency is approximately twice of that of the second frequency. The corresponding fundamental cycle period is therefore 10.7 years, the reciprocal of the fundamental frequency.

Similarly, annual profit data of the world airline industry between 1978 and 2002 were analyzed, and the fundamental frequency of the world airlines was found to be 0.099/year. Again, the magnitude is about 6dB higher or in other words twice stronger than that of the second frequency. Correspondingly, the fundamental cycle period of the profitability of the world airline industry is 10.1 years.

B. Hypothesis and Estimation of Empirical Profitability Models of Airline Industries

The profit oscillations of the U.S. airline industry since deregulation resembled an undamped second-order system (Fig. 3). Assuming the profitability of airline industry can be modeled as an undamped second-order system, the general form of the profitability model is

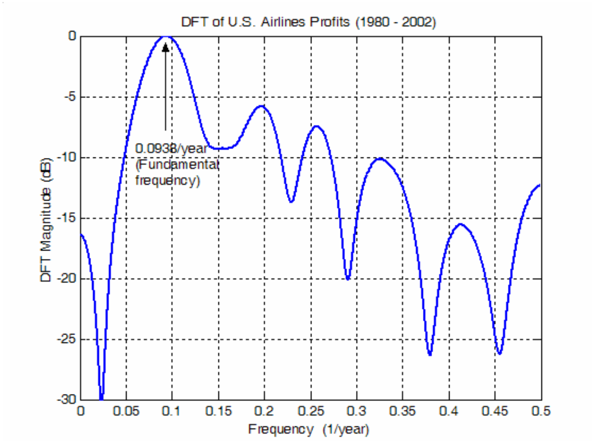

Figure 7. Discrete Fourier Transform of Annual Profits of the U.S. Airline Industry in 1980-2002.

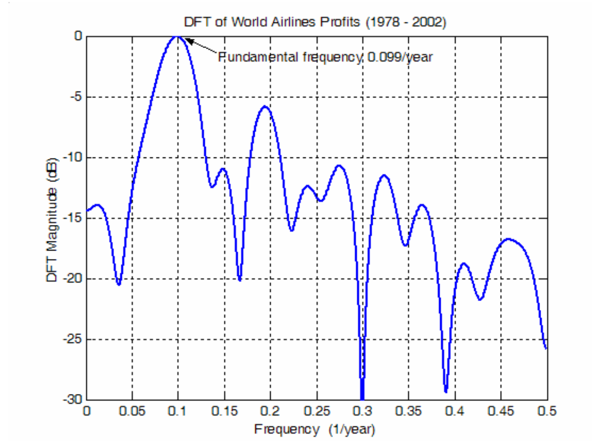

Figure 8. Discrete Fourier Transform of Annual Profits of the World Airline Industry in 1978-2002.

$$x(t) = Ae^{(t-t_0)/\tau} \sin\left(\frac{2\pi(t-t_0)}{T}\right) \tag{1}$$

where *x(t)* is the industry profit or loss measured in billions of constant 2000 dollars; *T* is the fundamental cycle period of profitability of airline industry; τ is the e-folding time indicating how rapidly the amplitude grows; *t* is the chronicle year; t_0 is the time instant the system crosses zero; and *A* is the amplitude of profit oscillation. Detailed derivation of Eq. (1) can be found in Chapter 2 of Ref. 8, pages 23-27.

Nonlinear least square regression was employed to estimate the net profit model specified in Eq. (1) from industry profit data. The profit data were evaluated in constant 2000 dollars in regression and the best estimation was obtained through iterations. The fundamental cycle periods identified by DFT analysis were served as initial values of *T* in Eq. (1) for the U.S. and world airline industries respectively to initiate the iteration and assure the solution convergence.

C. Profitability Model of the U.S. Airline Industry before Deregulation

To represent the fact that the U.S. airline industry was profitable most of the time before deregulation (Fig. 3), the general profitability model in Eq. (1) was modified by adding an intercept. Further, since the profits exhibited nearly steady oscillating amplitude before deregulation, the exponential term was removed from Eq. (1) by assuming the e-folding time approximates infinity. Consequently, the modified profitability model is proposed below

$$x(t) = Ae^{(t-t_0)/\tau} \sin\left(\frac{2\pi(t-t_0)}{T}\right) + C_0 \tag{2}$$

where C_0 is the intercept.

Annual net profit data[4] of the U.S. airline industry between 1960 and 1979 were used to estimate the parameters in above equation. The estimate of profitability model of the U.S. airline industry before deregulation is provided in Eq. (3). The correlation coefficient is 0.59. The best-fit results of the profitability model in Eq. (3) are compared with the input data (net profits in 1960-1979) shown as yellow bars in Fig. 9. The model further forecast the profitability in subsequent decade. The projections are compared with respect to the industry net profits between 1980 and 1990, shown as gray bars in Fig. 9.

$$x(t) = -1.06 \sin\left(\frac{2\pi(t-1957.4)}{11.2}\right) + 0.904 \tag{3}$$

D. Profitability Model of the U.S. Airline Industry after Deregulation

Annual net profits[4] of the U.S. airline industry between 1980 and 2002 were used to estimate the profitability model of the industry after deregulation. The model was last estimated in 2004 and the result is provided in Eq. (4). The correlation coefficient is 0.88. Figure 10 compares the best-fit results and projections of the model with respect to the industry net profits in 1978-2004.

$$x(t) = -0.550e^{(t-1977.4)/7.86}\sin\left(\frac{2\pi(t-1977.4)}{11.3}\right) \tag{4}$$

1. *Impact of Deregulation on the Profitability of the U.S. Airline Industry*

Deregulation in 1978 had a profound influence on the U.S. airline industry. Comparison of above two models indicates that deregulation changed the e-folding time significantly. The pre-deregulation model in Eq. (3) implies an infinite e-folding time, while this parameter becomes finite in Eq. (4) for post-deregulation circumstance. As a result, dramatically different behavior was witnessed before and after deregulation. Figure 9 illustrates an oscillation with constant amplitude whereas Figure 10 projects the industry profit to oscillate with increasing amplitude. Moreover, the oscillation amplitudes differ in magnitude as well. The amplitude of profit oscillation before deregulation is approximately 1 billion dollars, much lower than the amplitude in post-deregulation case (Fig. 10).

However, comparisons of the two models reveal that the fundamental cycle periods before and after deregulation were almost identical, approximately 11 years. This suggests that although deregulation had a strong influence on the oscillation amplitude, it did not change the fundamental profit cycle period of the U.S. airline industry.

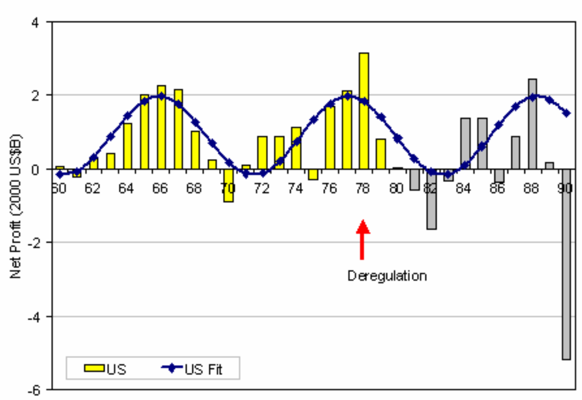

Figure 9. Comparison of Best-fit Results and Projections of Profitability Model of the U.S. Airline Industry before Deregulation with Respect to Industry Net Profits in 1960-1990.

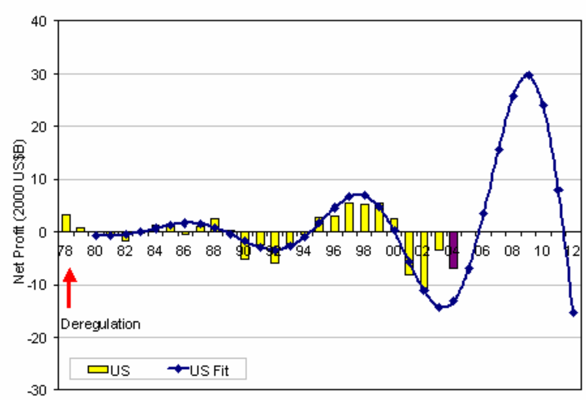

Figure 10. Comparison of Best-fit Results and Projections of Profitability Model of the U.S. Airline Industry after Deregulation with Respect to Industry Net Profits in 1978-2004.

2. *Impact of September 11 on the Profitability of the U.S. Airline Industry*

The September 11 terrorist attack had severely affected the air transportation system in the United States. To evaluate its impact on profit cyclicality, the profitability model was estimated again in Eq. (5) using the net profit data between 1980 and 2000. The correlation coefficient is 0.83. The best-fit results of the model as well as future projections are shown in Fig. 11 in comparison with industry profit outcomes till 2004.

$$x(t) = -0.728e^{(t-1976.5)/9.82}\sin\left(\frac{2\pi(t-1976.5)}{12.0}\right) \tag{5}$$

As seen from Fig. 11, the profit cyclicality is not highly dependent on the September 11 event. Comparison of amplitudes in Fig. 10 and Fig. 11 indicate that the event exacerbated the profit oscillation. However, close examination of Eq. (3) through Eq. (5) shows that the fundamental cycle period T of industry profitability did not vary significantly.

E. Profitability Model of the World Airline Industry

Following the same methodology, profit data between 1978 and 2002 from ICAO[5], evaluated in constant 2000 U.S. dollars, were used to estimate the profitability model of the world airline industry. The model was last estimated in 2004 and the result is presented in Eq. (6). The correlation coefficient is 0.84. Figure 12 shows the best-fit results of the model and projections in comparison with profits of the world airlines between 1978 and 2003.

$$x(t) = -3.00e^{(t-1978.9)/14.9} \sin\left(\frac{2\pi(t-1978.9)}{10.5}\right) \tag{6}$$

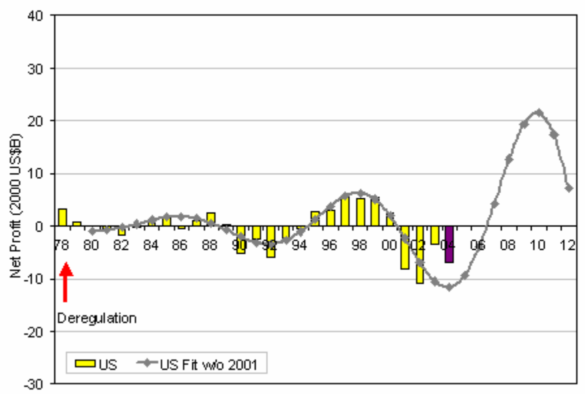

Figure 11. Comparison of Best-fit Results and Projections of Profitability Model of the U.S. Airline Industry after Deregulation with Data Only before 2001.

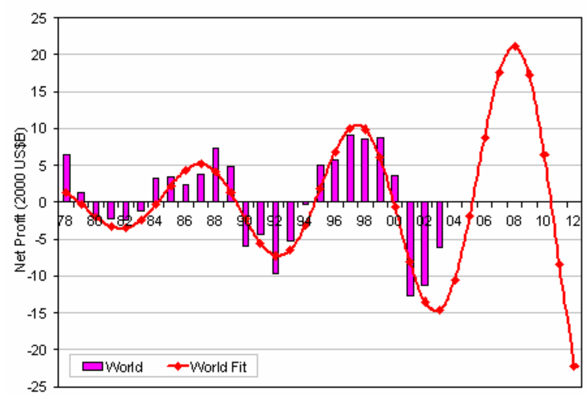

Figure 12. Comparison of Best-fit Results and Projections of Profitability Model of the World Airline Industry with Profit Data in 1978-2003.

F. Assumptions and Limitations of Empirical Profitability Models

It is worth to note that although the profitability models estimated above have obtained reasonably good correlation with historical profit data, above empirical models are not able to address causality and/or future constraints. It is clear that future industry growth will be limited at some point, probably by capital investment as the industry becomes less-appealing to investors due to losses in the down cycle, and/or by capacity and traffic demand as the system reaches the limit of the national aerospace system in the up cycle. Caution must be taken in applying these models to predict future system behavior and interpreting the projection results. Nevertheless, these models offer insight on the profit cyclicality of airline industries.

III. Parametric Model for Capacity

It is known that the presence of phase lag or delay in a control system causes oscillations and tends to make the system less stable. Two potential sources of phase lag were observed through extensive data examination: (1) lag between capacity response and profits, and (2) lag between cost adjustment and profits. This section analyzes the relationship between capacity and profitability, and discusses a parametric model based on the capacity hypothesis. The impact of lag between cost adjustment and profitability will be discussed in the next section.

A. Data Analysis of World Commercial Jet Orders and Deliveries

The relationship between industry profitability and world commercial jet orders and deliveries is illustrated in Fig. 13 through Fig. 15. Figure 13 depicts the world commercial jet airplane orders and deliveries to scheduled passenger and cargo airlines operating worldwide as recorded by ICAO[5]; approximately a two-year time shift can be observed between aircraft orders and deliveries. Figure 14 describes the relationship between world aircraft deliveries and net profits; a delay of approximately three years is observed between delivery peaks and profit peaks.

To assess the average delay, annual deliveries were further regressed with respect to annual profits and traffic (RPK) with several years of delay assumed. As shown in Eq. (7), the delivery in year t has the best correlation when average three years of delay was assumed for RPK and profit. The correlation coefficient is 0.90.

$$Delivery_t = 87 + 0.29\, RPK_{t-3} + 0.027\, Profit_{t-3} \tag{7}$$

where RPK is in billions, profit in billions of dollars and Delivery in aircraft units. The regression results are shown in Fig. 14 for comparison.

In addition to the delay observation, an asymmetric effect was found between world aircraft orders and net profits. Figure 15 shows that the world annual aircraft orders either grow with the profits of prior year when the industry is profitable or follow a flat trend otherwise. A first-order approximation of this asymmetric effect indicates that the slope of aircraft orders with respect to the prior-year profits averages about 147 airplane orders per year for each billion dollars of profits, whereas the flat trend is about 350 airplane orders per year regardless of the magnitude of losses.

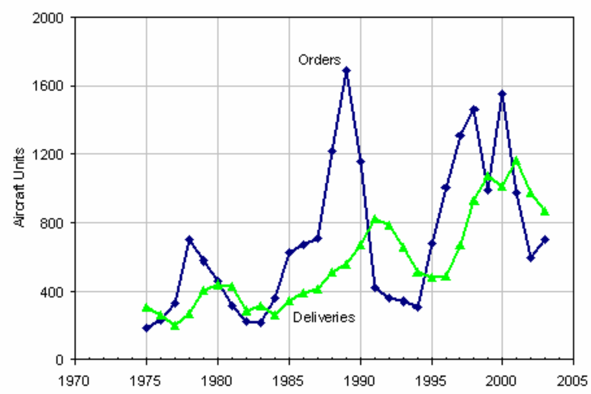

Figure 13. World Commercial Jet Aircraft Orders and Deliveries[5].

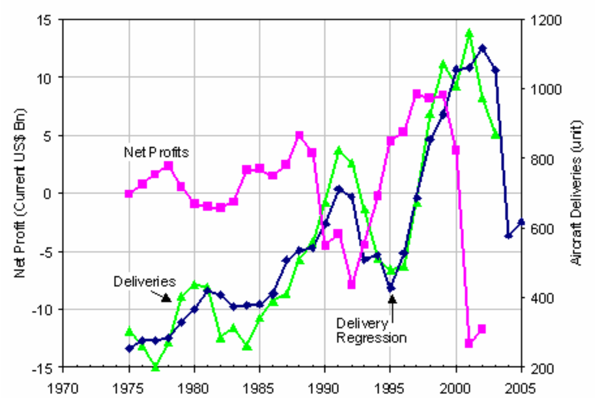

Figure 14. World Aircraft Deliveries and World Airline Net Profits[5].

B. Capacity Hypothesis and Parametric Model for Capacity

The existence of phase lag or delay will cause the system to oscillate. From above data analysis, approximately 3-year delay was observed between aircraft deliveries and profitability of the world airline industry. The capacity hypothesis was that the phase lag in capacity response caused the oscillation in profits of airline industry.

A parametric model was developed based on the capacity hypothesis and the block diagram is shown in Fig. 16. The output of the model is the capacity offered by the system that has units of available seat-miles (ASM). The input of the model is the demand, i.e., desired capacity, which also has units of available seat-miles. The difference between the demand and the capacity is capacity shortfall, which again has units of available seat-miles. Airlines order airplanes based on the capacity shortfall and their ordering strategies. The control gain K in the model represents the overall aggressiveness in the ordering process, and has units of ASM ordered per year per unit ASM shortfall. The delay D represents the lag between capacity shortfall and deliveries in the system and has units as years. Assuming airlines' pricing activity is based on capacity shortfall, capacity shortfall is correlated with profits through constant C, and the delay D also represents the lag between profits and deliveries. Because of the delay, the new deliveries will not be added into the total capacity until D years later. The closed-loop transfer function of the capacity parametric model is

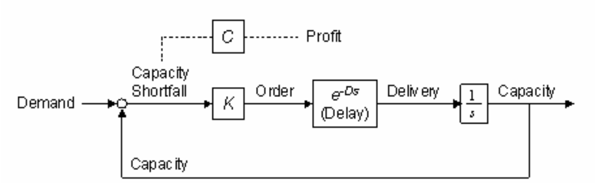

Figure 16. Block Diagram of Parametric Model for Capacity.

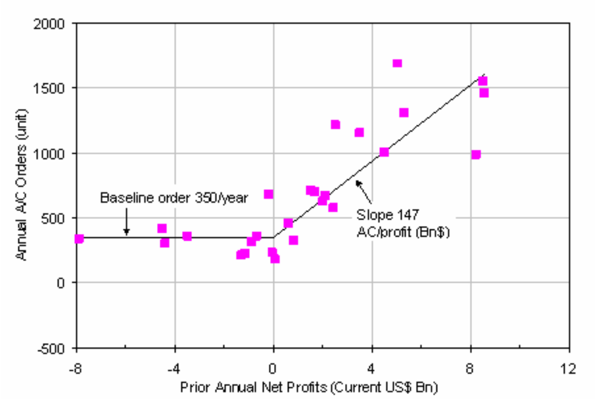

Figure 15. Asymmetric Effect between World Aircraft Orders and World Airlines Net Profits.

$$H(s) = \frac{Ke^{-Ds}/s}{1 + Ke^{-Ds}/s} \tag{8}$$

C. Stability of Parametric Model for Capacity

1. Root-Locus Analysis of System Stability

A root-locus analysis was performed to analyze the stability of the capacity parametric model and the main branch of the root-locus is shown in Fig. 17. The critical point, the point where the main branch of the root-locus crosses the imaginary axis, holds the relationship presented in Eq. (9).

$$\begin{cases} \omega_{crit} = \dfrac{2\pi}{T_{crit}} = \dfrac{\pi}{2D} \\ T_{crit} = 4D \\ K_{crit} = \omega_{crit} = \dfrac{\pi}{2D} \end{cases} \tag{9}$$

where ω_{crit} is the critical frequency at which the system oscillates with constant amplitude, T_{crit} is the critical cycle period and K_{crit} is the critical gain corresponding to ω_{crit} respectively.

The relationship between the system stability and the values of delay and gain implied by the root-locust analysis is better illustrated in Fig. 18. The line in the figure indicates the boundary that maintains the system stability. Systems on the boundary will just oscillate with constant amplitude and hold the relationship described in Eq. (9). Shown in Fig. 17, the system will become unstable when its poles cross over the imaginary axis and enter into the right-hand side of s-plane, i.e., when $\omega > \omega_{crit}$ and/or $K > K_{crit}$. This corresponds to the area in Fig. 18 that is above the stability boundary. Systems in this area will oscillate exponentially. The area below the stability boundary represents the stable region and corresponds to the left-hand side of s-plane in Fig. 17.

Therefore, the system stability is dependent on the delay and gain values and its location on the map in Fig. 18. To understand the profit stability of airline industry, it is necessary to determine the parameters that represent the U.S. and world airline industries and locate them on the map.

2. Determining Parameters in Parametric Model for Capacity

In order to use profit data to calculate the delay and gain values in the capacity parametric model, it is necessary to relate profits to capacity shortfall. A linear relationship was assumed in Eq. (10) that the aggregate industry profits are proportional to the capacity shortfall (Fig. 16).

$$Profit = C\ (Demand - Capacity) \tag{10}$$

Such assumption implies that profit has the same characteristic equation as capacity shortfall, and consequently has the same oscillation frequency and damping ratio as capacity shortfall. Therefore, it enables ones to use the fundamental cycle period T and e-folding time τ estimated in the previous section to calculate the delay and gain values from Eq. (11) below. Detailed

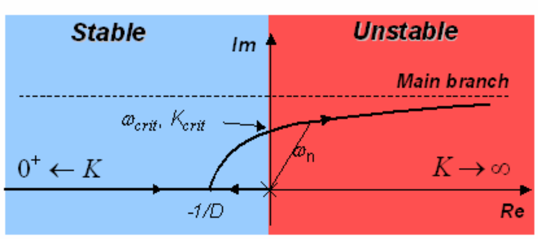

Figure 17. Main Branch of the Root-Locus of Parametric Model for Capacity.

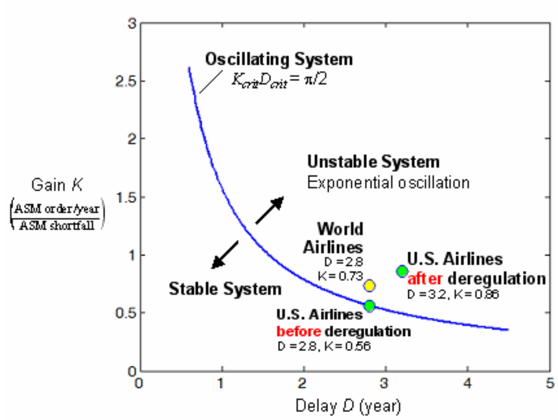

Figure 18. System Stability and Delay and Gain Values in Parametric Model for Capacity of the U.S. and World Airline Industries.

derivations can be found in Chapter 4 of Ref. 8 on pages 42-45.

$$\begin{cases} \tan(\omega_d D) = \tan\left(2\pi D/T\right) = \dfrac{\omega_d}{\xi\omega_n} = -\dfrac{2\pi\tau}{T} \\ K = \dfrac{\omega_d}{e^{D\xi\omega_n}\sin(\omega_d D)} = \dfrac{2\pi}{Te^{-D/\tau}\sin\left(2\pi D/T\right)} \end{cases} \tag{11}$$

Using Eq. (11), the delay and gain values for the U.S. and world airlines were computed from the e-folding time τ and fundamental cycle period T that were estimated previously. The results are summarized in Table 1, including the critical gain that is calculated with respect to delay using Eq. (9). The delay and gain values of the U.S. and world airline industries are also plotted in Fig. 18.

Seen from the table, the computed delay for the world airline industry is 2.8 years. This is consistent with the observed average 3-year delay between the profits of the world airline industry and airplane deliveries. The consistency indicates that capacity could influence profits. The gain for the world airline industry is 0.73 annual ASM ordered per ASM shortfall, that is, 73% of capacity shortfall is fulfilled annually. The gain is about 30% larger than the critical value. Similarly, the computed delays for the U.S. airlines before and after deregulation are consistent or close to the observed average 3-year delay for world airplane deliveries. However, the gain for the U.S. airline industry after deregulation is approximately twice the critical gain. By contrast, the computed gain for the U.S. airline industry before deregulation is equal to the critical value, representing a system that oscillates with constant amplitude. As seen from Fig. 18, the point representing the U.S. airline industry before deregulation is located right on the stability boundary, whereas the points for the U.S. airline industry post deregulation and the world airline industry all fall in the unstable region. Moreover, the point representing the U.S. airline industry post deregulation is positioned further from the stability boundary than that for the world airline industry, indicating it's more unstable than the latter.

Table 1. Delay and Gain Estimates in the Parametric Model for Capacity of the U.S. and World Airline Industry.

Airline Industry	T	τ	D	K	K_{crit}
	Year			$\left(\frac{\text{ASM order/year}}{\text{ASM shortfall}}\right)$	
World	10.5	14.9	2.8	0.73	0.56
U.S. before Deregulation	11.2	∞	2.8	0.56	0.56
U.S. after Deregulation	11.3	7.86	3.2	0.86	0.49

3. Factors Contributing to Delay and Gain Values in Parametric Model for Capacity

The delay in the airline industry primarily consists of the decision time in placing orders, order processing time and manufacturing lead-time.

Factors contributing to the high gains may include:

- Optimism in total capacity projection that amplifies the capacity shortfall;
- Collective market share perspective is greater than 100%. The collective market share perspective represents the aggregate effect of individual airlines' projections in market share. For individual airlines, the management usually makes fleet plans based on the market share and traffic projections. Consequently, the collective market share perspective in each competing O-D market and in total capacity could easily exceed 100%, resulting over-capacity at industry-level;
- Aggressiveness when the manufacturers pursue orders. This can happen when a manufacturer offers special deals to particular airlines or markets for the sake of market penetration and/or the market share of the manufacturer;
- Exogenous factors. Because of the simplicity of the parametric model, the gain has lumped impacts of exogenous factors, such as, the positive impact of high GDP growth on traffic and the negative impact of economic recession and/or war on demand, as well as the influence of fuel price fluctuations on profits.

D. Simulation of Parametric Model for Capacity of Airline Industries

1. Simulation of Capacity of the U.S. Airline Industry

The capacity of the U.S. airline industry was simulated by running the capacity parametric model (Fig. 16) with delay and gain values from the U.S. post-deregulation condition (Table 1). The input demand was assumed to grow at 4% per year, the average ASM growth rate of the U.S. airline industry since deregulation (Fig. 1). The simulation starting time was 1980 when the industry profit was near zero, implying certain equilibrium achieved between demand and supply.

Figure 19 shows the simulation results of demand and capacity in comparison with ATA capacity data. Figure 20 shows the results of capacity shortfall plus industry net profits to illustrate the relationship between capacity shortfall and profits. Seen from Fig. 20, according to the simple capacity parametric model, the industry was approximately 550 billion ASMs under-capacity in 1998 whereas approximately 1,000 billion ASMs over-capacity in 2003; the capacity shortfall has grown through the cycles. The exponentially oscillating behavior in capacity shortfall is generally consistent with industry profits. However, the capacity simulation in Fig. 19 overshoots the observed variation in capacity data. This indicates that capacity shortfall alone is not sufficient to explain industry profit oscillations.

As discussed before, aggregate industry profits were related to capacity shortfall in order to determine the delay and gain values in the parametric model. If the behavior were solely due to capacity shortfall, constant *C* in Eq. (10) would have the implication of cost or incentive for adding or removing additional capacity. From the simulations results in Fig. 20, constant C can be estimated by regressing the profit data with respect to capacity shortfall via least-square. The value of constant *C* was found to be approximate 1 cent (2000$) per ASM in capacity shortfall, implying that the cost or incentive for adding or removing one available seat-mile to fulfill the capacity shortfall will lead to approximately one cent (2000$) in loss or profit. It should be pointed out that such estimation is preliminary given the simplicity of the model; however, it illustrates the potential interaction between capacity and profit.

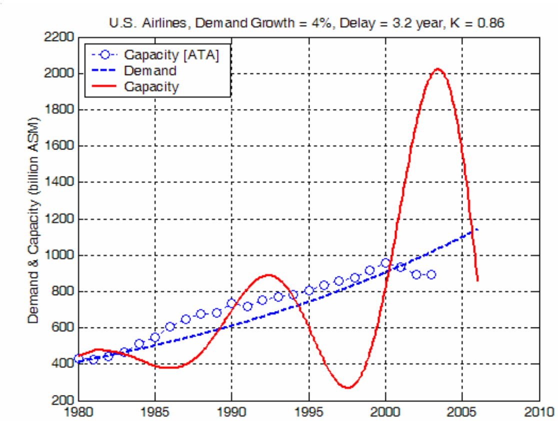

Figure 19. Simulation of Demand and Capacity of the Capacity Parametric Model of the U.S. Airline Industry.

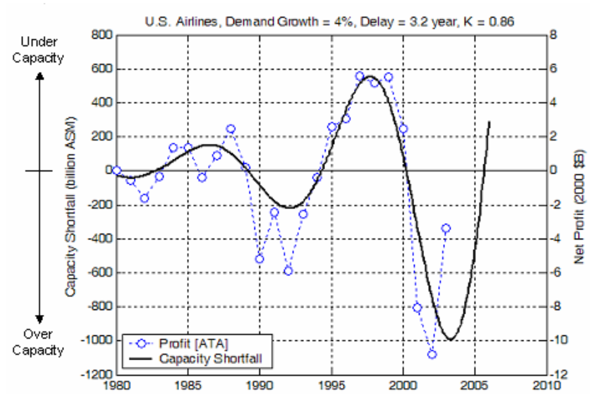

Figure 20. Simulation of Capacity Shortfall of the Capacity Parametric Model of the U.S. Airline Industry.

2. Simulation of Capacity of the World Airline Industry

The capacity of the world airline industry was also simulated by setting the delay and gain in the parametric model to the values for the world airlines in Table 1. The demand growth rate was assumed to be 4.7%, the average worldwide ASK growth rate (Fig. 5). Again the simulation starting time was 1980.

Simulation results of demand and capacity of the world airlines are shown in Fig. 21 in comparison with ICAO capacity data. The model also simulates the aircraft orders in terms of ASMs, as shown in the block diagram (Fig. 16). In order to compare the results with historical airplane order data, simulated aircraft orders in ASMs were converted to aircraft unit orders by dividing the average aircraft utility. The average aircraft utility of the U.S. airlines, that was 190 million ASMs per aircraft per year as discussed in Appendix A of Ref. 8, was used in the conversion. The converted order simulations are shown in Fig. 22, in comparison with the world airplane order data from ICAO and the baseline order that was 350 aircraft per year shown in Fig. 15. Again, the capacity simulation in Figure 21 overshoots the observed variation in capacity data. Seen from Figure 22, the simulation of orders is generally consistent with world aircraft orders. The average of the simulation results is above zero, partially reflecting the asymmetric effect between profitability and aircraft orders shown in Fig. 15.

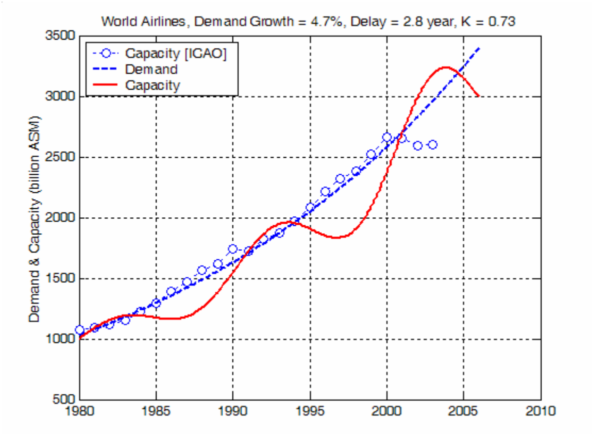

Figure 21. Simulation of Demand and Capacity of the Capacity Parametric Model of the World Airline Industry.

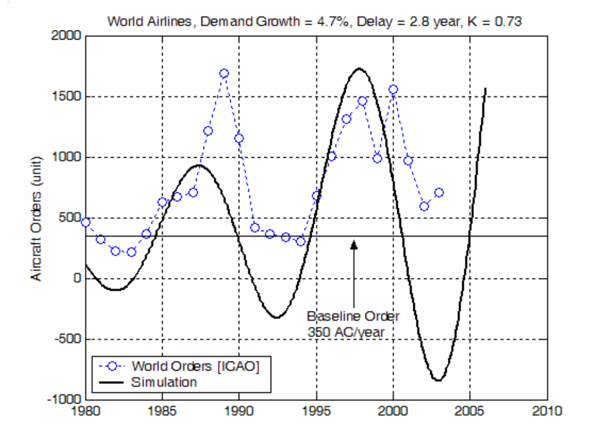

Figure 22. Simulation of Capacity Shortfall of the Capacity Parametric Model of the World Airline Industry.

E. Mitigating System Oscillations

The parametric capacity model was also used to explore potential ways to mitigate system oscillations. The stability relationship shown in Fig. 18 suggests that the system could be stabilized by reducing delay and gain below the stability boundary. As an illustration, simulations were performed with different delays while holding the gains unchanged, and results of different delay values are shown in Fig. 23 for the U.S. airline industry and in Fig. 24 for the world airline industry. The results indicate that if the gain is held unchanged, the capacity of the U.S. airline industry would become stabilized if the delay were reduced from 3.2 years to 1.8 years. Similarly, the world capacity would stabilize if the delay were reduced from 2.8 year to 2.2 years.

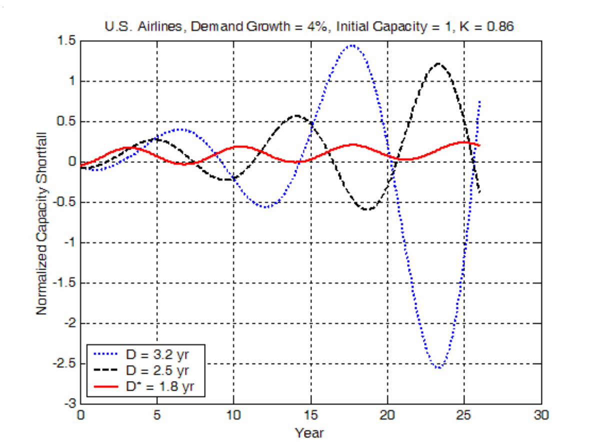

Figure 23. Mitigating Capacity Oscillations of the Capacity Parametric Model of the U.S. Airline Industry.

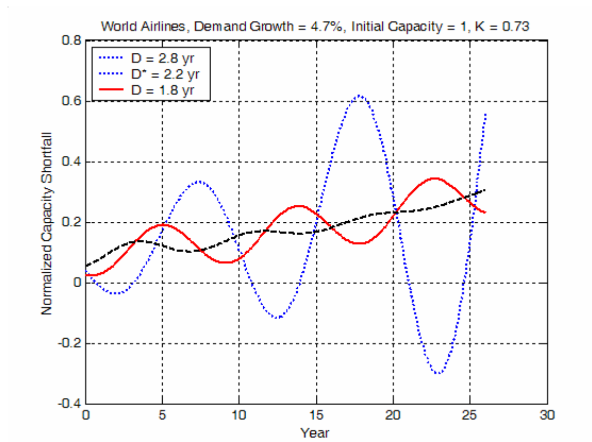

Figure 24. Mitigating Capacity Oscillations of the Capacity Parametric Model of the World Airline Industry.

IV. Parametric Model for Cost

A. Unit Net Profit Analysis

Assuming the unit net profits of the U.S. airline industry after deregulation (Fig. 4) resembled an undamped second-order system, the unit net profit model of the industry was estimated in Eq. (12) using the unit net profit data between 1980 and 2002. The correlation coefficient is 0.85. Figure 25 shows the best-fit results and projections of the model in comparison with industry unit net profits through 2003.

$$u(t) = -0.110 e^{(t-1977.6)/9.78} \sin\left(\frac{2\pi(t-1977.6)}{11.2}\right) \quad (12)$$

where *u(t)* is in cent/ASM in constant 2000 dollars.

B. Cost Hypothesis and Parametric Model for Cost

1. Cost Hypothesis

Figure 26 depicts the RASM (passenger revenue per ASM) and CASM (operating expense per ASM) of the U.S. major and national passenger carriers recorded by DOT[9] and ATA[10], where, CASM has been adjusted with respect to passenger services based on ATA Airline Cost Index[10]. The methodology of cost adjustment is provided in Appendix B of Ref. 8. Seen from Fig. 26, RASM has decreased on average 1.7% per year between 1980 and 2000, while CASM has decreased at 2% annually. The fluctuations in RASM were followed by the fluctuations in CASM with about one year delay. RASM dropped significantly by about 1.3 cent or 14% in 2001 because of the industry crisis then. Correspondingly, CASM dropped by 1 cent or 10% in 2003 from 2001 level.

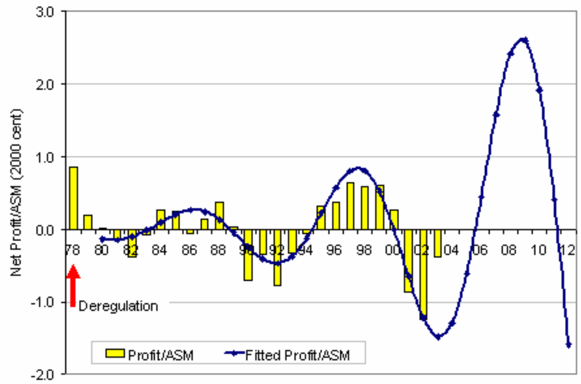

Figure 25. Best-fit Results and Projections of the Unit Net Profit Model of the U.S. Airline Industry after Deregulation in Comparison with Unit Profit Data through 2003.

Figure 27 shows the unit operating expenses and unit net profits of all U.S. airlines after deregulation. Comparing to Fig. 26, a delay of approximately three years is observed between the peaks of unit operating expenses and the peaks of unit net profits as well as between the troughs of these two variables.

The cost hypothesis was that the phase lag between cost adjustment and profits caused system oscillation.

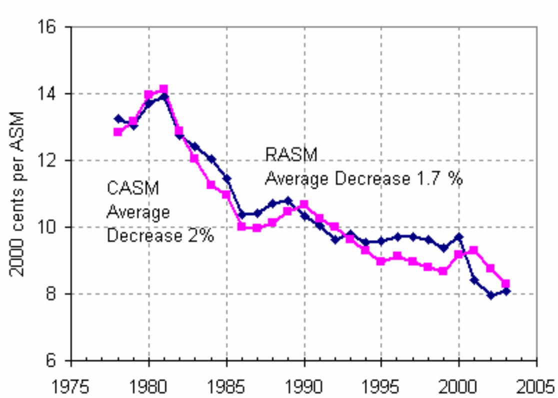

Figure 26. RASM and CASM of the U.S. Major and National Passenger Carriers[9, 10].

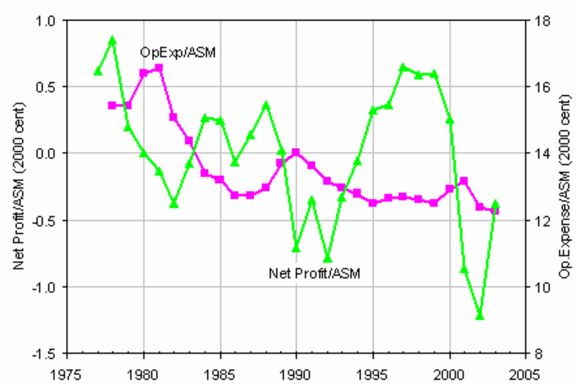

Figure 27. Unit Operating Expenses and Unit Net Profits of the U.S. Airline Industry.

2. Parametric Model for Cost

A parametric model was developed based on the cost delay hypothesis with the block diagram shown in Fig. 28. According to Appendix B of Ref. 8, CASM was separated into two components: CASM1 – profit-sensitive component and CASM2 – less profit-sensitive part. The system has two inputs: RASM and CASM1; both having long-term decreasing trends (Fig. 26). The difference between RASM and CASM gives the output – profit per ASM (PASM). Based on PASM, cost

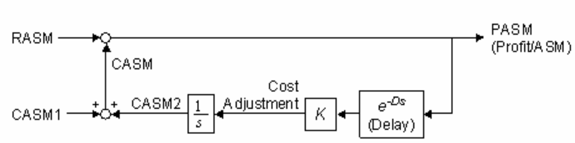

Figure 28. Block Diagram of Parametric Model for Cost.

adjustment is made due to labor contract negotiation, the competition need, etc. However, because of the delays in the system such as contract negotiation time, the cost adjustment will not take effect immediately but *D* years later. The control gain *K* in the model represents the effect of PASM on cost adjustment and has the units of cent/ASM cost adjustment per year per unit cent/ASM profit. The closed-loop transfer function with respect to RASM is

$$H(s) = \frac{1}{1 + Ke^{-Ds}/s} \tag{13}$$

Table 2. Delay and Gain Estimates in Parametric Model for Cost of the U.S. Airline Industry.

Airline Industry	T	τ	D	K	K_{crit}
	Year			$\left(\frac{\text{Cent/ASM cost/year}}{\text{Cent/ASM profit}}\right)$	
U.S. after Deregulation	11.2	9.78	3.1	0.78	0.50

Comparing Eq. (8) and Eq. (13), one can see the two parametric models share the same characteristic equation. Therefore, Equation (11) was able to be used again to obtain the delay and gain values in the cost parametric model that are summarized in Table 2 and Fig. 29. Figure 29 shows that the U.S. airline industry post-deregulation again falls in the unstable region

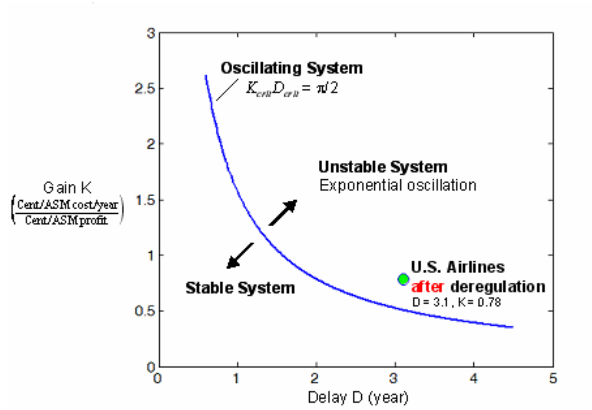

Figure 29. System Stability and Delay/Gain Values in the Cost Parametric Model of the U.S. Airline Industry after Deregulation.

C. Simulation of Parametric Model for Cost

Simulations of the cost parametric model were carried out by running the model with the delay and gain values determined above. The model was calibrated with unit net profits of the U.S. airline industry in 1980-2000, assuming RASM and CASM decreasing at 1.7% and 2% per year respectively. Results of calibration simulation are shown in Figure 30 and 31 in comparison with historical data.

Figure 32 and 33 summarize another simulation, in which, RASM was further subject to a 14% step decrease in 2001 to simulate the industry crisis in 2001. Seen from Fig. 33, the exponentially oscillating behavior in PASM is consistent with industry unit net profits.

Overall, the simulation results indicated that the cost parametric model captures the system behavior reasonably well. The model identified cost adjustment is another potential driving factor of the system behavior, in additional to the capacity response factor.

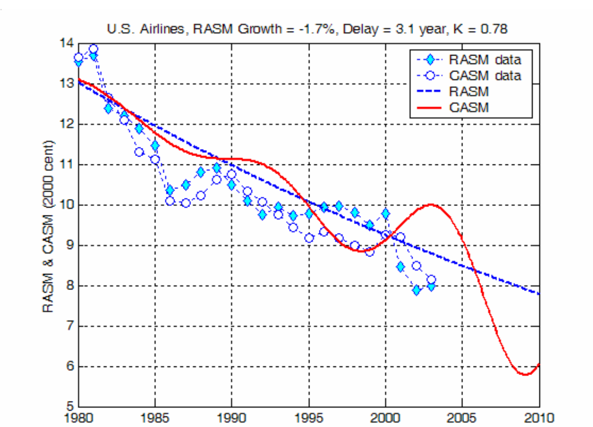

Figure 30. Simulation of Cost/ASM of the Cost Parametric Model of the U.S. Airline Industry.

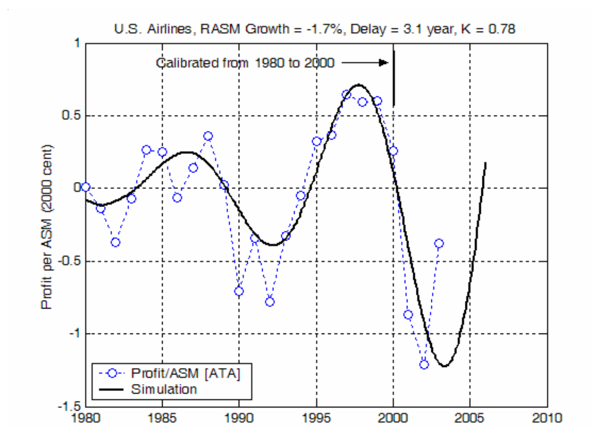

Figure 31. Simulation of Profit/ASM of the Cost Parametric Model of the U.S. Airline Industry.

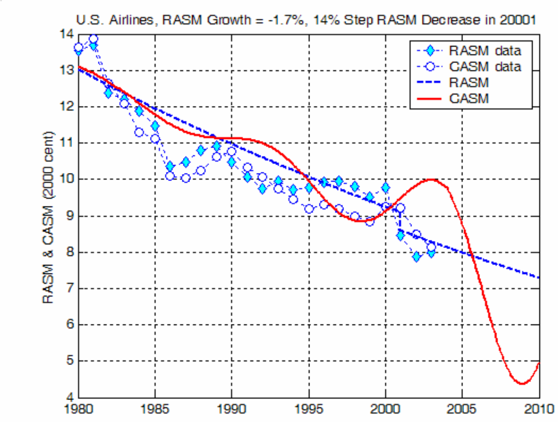

Figure 32. Simulation of Cost/ASM of the Cost Parametric Model of the U.S. Airline Industry with Step RASM Decrease in 2001.

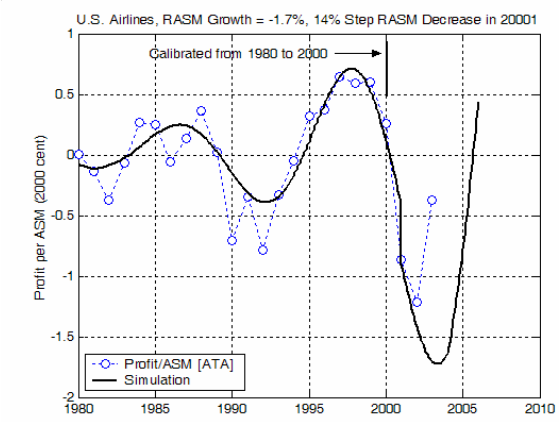

Figure 33. Simulation of Profit/ASM of the Cost Parametric Model of the U.S. Airline Industry with Step RASM Decrease in 2001.

V. Coupling Capacity and Cost Effects

A. Coupled Model Combining Capacity and Cost Effects

Shown in Fig. 34 is the coupled model that combines capacity and cost effects. The model was formed primarily by joining the capacity model in Fig. 16 and the cost model in Fig. 28. The output of the model is the total profit, the product of capacity and unit profit (PASM). The capacity and cost effects are coupled through two feedbacks from the profit: one fed to the order aggressiveness K_1 and the other to the profit-sensitive part of CASM. Following the process described in Chapter 7 of Ref. 8, the model was calibrated with respect to the historical capacity, profit, PASM and CASM data of the U.S. airline industry between 1980 and 2000, with results summarized in Table 3.

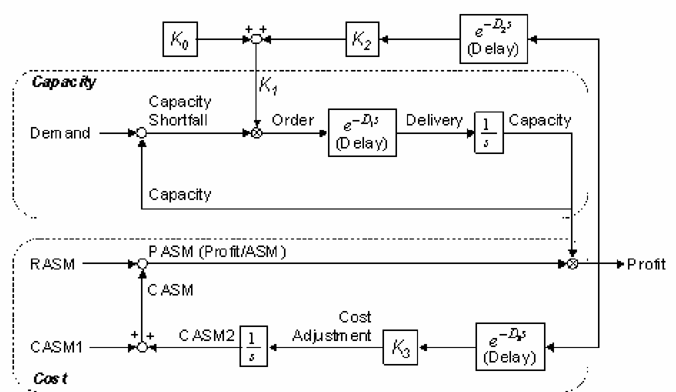

Figure 34. Block Diagram of the Coupled Model Combining Capacity and Cost Effects

B. Simulation Results

Figures 35 through 39 depict the simulation results of the calibrated model of the U.S. airline industry in terms of capacity, fleet size, CASM, profit, and aircraft orders. The simulation assumed ASMs growing at 4%, RASM decreasing at 1.7% and CASM1 decreasing 2% per year respectively, i.e., each of them evolving along its respective trend shown in Fig. 1 and Fig. 26. The simulation of the U.S. fleet (Fig. 36) was obtained by dividing the capacity by the average aircraft utility of the U.S. airline industry (190 million ASMs per aircraft per year[8]). Figure 39 compares the simulation of U.S. aircraft orders with 35% of world aircraft orders. The 35% is roughly the share of U.S. orders of world total according to the Boeing Current Market Outlook 2003[11]. To verify the reasonableness of parameter estimates, particularly the value of K_2, the assumed U.S. orders (35% of world orders) are further plotted against prior-year profits in Fig. 40 as well as the simulation results. The figure shows that when the airlines are profitable, the slope of simulated aircraft orders with respect to the profits is in the neighborhood of the observed slope from actual data shown in Fig. 15, suggesting the estimate of K_2 – effect of profitability on order aggressiveness is reasonable.

Overall, as can be seen from the figures, the coupled model interprets the industry dynamics reasonably well in terms of capacity growth, fleet size, CASM, profitability, and the effect of profitability on airplane orders. The coupled model explains industry dynamics better than individual capacity or cost parametric models, suggesting that the system behavior is driven by the joint effects of capacity response and cost adjustment.

Table 3. Summary of Parameters in the Coupled Model of the U.S. Airline Industry.

Parameter	Description	Value
D_1	Delay between orders and deliveries	2.2 years
D_2	Delay between profits and profit-driven orders	1 years
D_3	Delay between profits and cost adjustment	3.1 years
K_0	Baseline order aggressiveness	0.86 $\frac{\text{ASM order/year}}{\text{ASM shortall}}$
K_1	Overall order aggressiveness	$K_1 = K_0 + K_2(Profit_{t\text{-}D2})$
K_2	Order aggressiveness due to profitability	0.05 $\frac{\text{ASM order/year}}{\text{ASM shortall}} \Big/ \text{Billion \$ profit}$
K_3	Effect of total profits on cost adjustment	0.11 $\frac{\text{Cent/ASM cost/year}}{\text{Billion \$ profit}}$

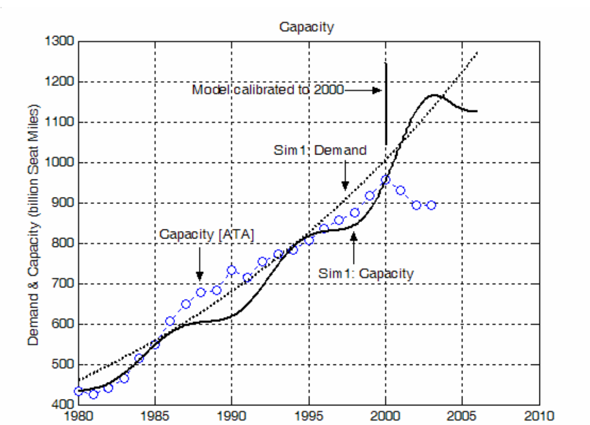

Figure 35. Simulation of Capacity of the Coupled Model of the U.S. Airline Industry.

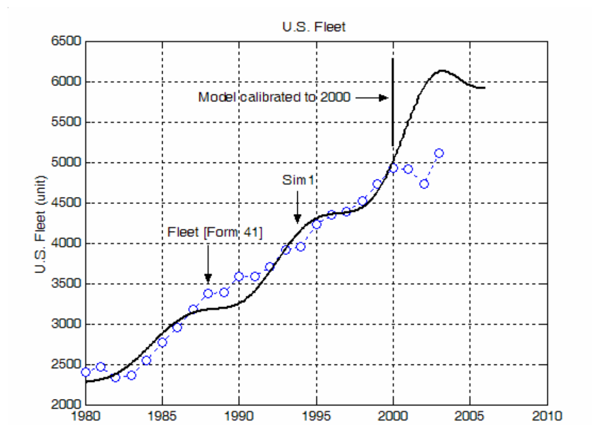

Figure 36. Simulation of Fleet of the Coupled Model of the U.S. Airline Industry.

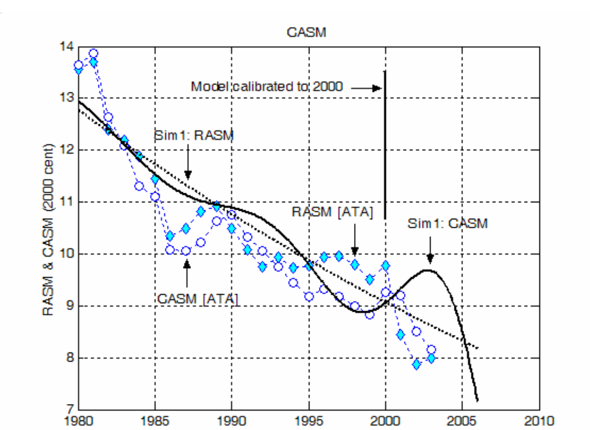

Figure 37. Simulation of CASM of the Coupled Model of the U.S. Airline Industry.

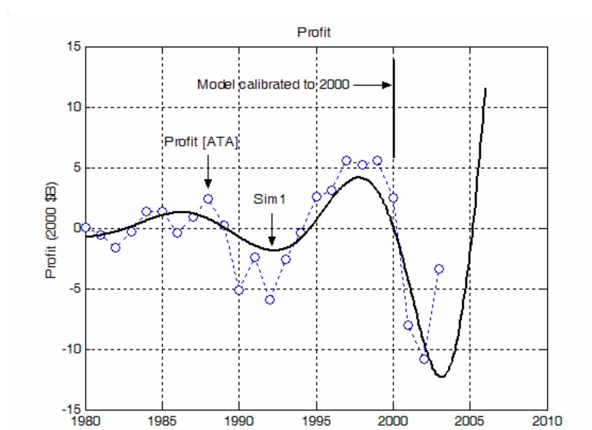

Figure 38. Simulation of Profitability of the Coupled Model of the U.S. Airline Industry.

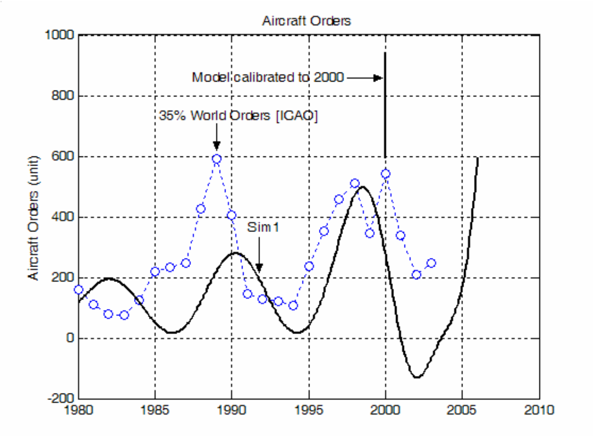

Figure 39. Simulation of Aircraft Orders of the Coupled Model of the U.S. Airline Industry.

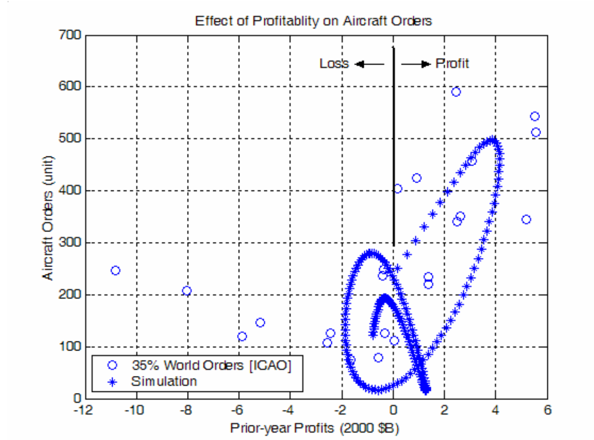

Figure 40. Simulation of Effect of Profitability on Aircraft Orders of the U.S. Airline Industry.

VI. Conclusion

This paper discusses the financial dynamics of the airline industry by identifying the fundamental cycle periods of profitability and their driving factors. Assuming the industry profit cycles could be modeled as an undamped system, the fundamental cycle period was found to be 11.3 years for the U.S. airline industry and 10.5 years for the world airline industry. An empirical profitability model was last estimated based on the fundamental cycle period, and the results revealed that such cycle period is endogenous. Deregulation did not change the cycle period however had a strong influence on the oscillation amplitude. Similarly, exogenous shocks like the September 11 terrorist attack exacerbated the industry profitability but did not significantly change the profit cycle period. Although the empirical models offer insights on profit cyclicality of airline industry, it does not address causality and/or constraints where the industry growth will likely reach in the future. Therefore, care must be taken in applying the models to predict future system behavior

To analyze the causes of profit cyclicality, parametric models were developed under the hypothesis that phase lag in the system caused the profit oscillations; and two hypotheses, lag in capacity response and lag in cost adjustment were studied. Analysis of the parametric model of capacity response indicated that the system stability depends on the delay between aircraft orders and deliveries and the aggressiveness in airplane ordering. Exaggerated capacity response was observed in the simulation as the gain in the model has lumped impacts of exogenous factors, suggesting capacity shortfall alone cannot fully explain the industry dynamics. The model also indicates reducing delay may help to mitigate system oscillations. Simulation results of the parametric model regarding cost adjustment were consistent with profit observations. Finally, a coupled model was developed to study the joint effects of capacity and cost. Simulation results indicated that the coupled model explained industry dynamics better than individual capacity or cost models, suggesting that the dynamics of the industry is driven by the joint effects of capacity response and cost adjustment.

Acknowledgments

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