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Simulating revenue management in an airline market with demand segmentation and strategic interaction

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ABSTRACT
KEYWORDS: computer simulation, airline industry, revenue management, non-cooperative games, post-liberalisation strategy

This paper develops a computer simulation to investigate the consequences of revenue management by airlines on the Brazilian Rio de Janeiro–São Paulo route, in the period subsequent to the second phase of liberalisation of the industry in 1998. The model allows demand segmentation — namely, the typology of Belobaba ('Airline differential pricing for effective yield management', in Handbook of Airline Marketing, *McGraw-Hill, New York, 1998) — and airline strategic interaction — a revenue management game. Simulation results revealed gains in efficiency and non-global conditions of superiority in comparison with the extreme alternative of 'first come, first served' policy with uniform pricing.*

INTRODUCTION

> '[T]he computer supplies a viewing equipment to the economist in a manner analogous to the microscope for biologists (however, a great amount of work goes into setting up the 'specimens' to be observed). Beyond its use as a viewing instrument, it provides a possibility for the construction and running of experiments. It has a use as laboratory apparatus. The various uses of the computer are not substitutes for economic analysis or observation. They are nevertheless supplements of considerable power'. (Shubik, 1960)

This paper develops a computer simulation model to investigate the impacts and rationality of revenue management on the Brazilian Rio de Janeiro–São Paulo route. Economic regulation of the country's domestic industry has been liberalised by authorities since the early 1990s. As a result, airlines are in intense competition, although with much turbulence in terms of financial performance and stability.

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Revenue management has been extensively used by airlines on the route since price liberalisation, but so far there are few academic studies assessing its impacts in the Brazilian industry, and this was the main motivation for this research. The model conceived permits the analysis of its effects in market efficiency and constitutes one of the first computer simulation studies designed to reproduce revenue management on a real route under actual competitive circumstances, instead of an artificial market as in Belobaba and Wilson (1997).

Another relevant aspect is that some of the airlines have so far preferred not to perform revenue management on the route, opting for the traditional 'first come, first served' policy with uniform pricing. This alternative can be regarded as precisely the extreme opposite of revenue management — no product differentiation, price discrimination or seat-inventory control. In order to understand this unexpected pattern of behaviour, the paper promotes an investigation into airlines' competitive rationality towards revenue management by articulating the simulation with game theoretical modelling.

The simulation aimed to be a valid representation of the market on the route, by the definition of detailed characteristics of demand and supply, like the stochastic process of arrivals across time, actual schedules, aircraft size, fare products, etc. The two most significant features, however, were the modelling of the segmentation of demand using the typology of Belobaba (1998), and the presence of strategic interaction among airlines — what was called the 'revenue management game'. Model validation used historical input data and was followed by a design of experiments (simulation scenarios).

There are four sections in the paper: first, a historical background of the Brazilian airline industry and the route under analysis; secondly, details of the computer simulation, describing market and model characteristics, process of calibration and validation; thirdly, details of the experiments designed and the assessment of the revenue management in the market (impacts and rationality); and finally, the main conclusions.

THE BRAZILIAN AIRLINE INDUSTRY AND THE ROUTE FROM RIO DE JANEIRO TO SÃO PAULO: HISTORICAL BACKGROUND

The Brazilian domestic airline industry has been placed in a gradual and continuous process of economic liberalisation. Initiated at the end of the 1980s within a broader governmental programme for deregulation of the country's economy, this series of changes in the authorities' policy can be divided into three main periods: the first phase, with the stimulus of new airlines to enter the market and the introduction of lower and upper bounds for prices (1989–1997); the second phase, with more liberalisation of route entry and bounds (1998–2001); and the third phase, with virtually full deregulation (from August 2001).

As a result, an increase in the degree of competitiveness in the industry was recently observed; notably, the rivalry between airlines has led to severe price reductions and market expansion since 1998. This phenomenon was exacerbated on the Rio de Janeiro–São Paulo route — the country's densest flow, with a third of the profits of the whole domestic network.[1] Traditionally, it was closely associated with the cooperative structure formed by a cartel of majors (Varig, Vasp and Transbrasil), constituting a 39-year-old walk-on shuttle service, one of the most durable private institutions of air transport in the world. The cartel's rupture happened a few months after the announcement of the liberalisation measures of 1998.

Above all, one of the most important characteristics observed in the period was the tendency of price dispersion in a context of revenue management. As a technological innovation created by the North-American airlines in the adjustment to the deregulation of the 1970s, revenue management consists of the following three tools:[2] price discrimination, which is usually of a 'second-degree' sort, that is, based on demand self-selection (Botimer, 1996); product differentiation, which refers to the purchase restrictions ('fences') such as advance purchase, minimum stay, stay over Saturday nights, etc., in order to 'prevent passengers with higher values of willingness to pay from purchasing discount fare products' (Botimer, 1996); and finally, the techniques of seat-inventory control, that is, systems to maximise total revenue given the capacity of the airline in the market (eg. Belobaba, 1987).

Table 1 illustrates the relevance of revenue management in the post-liberalisation environment, presenting a simple measure of the degree of overall price dispersion on the route (the range between full fares and the maximum discount found in the market, in percentages). The table leads to the inferance that the second phase of liberalisation triggered a wave of high price dispersion, at least if measured by the maximum range of discounts. Associated with this tendency, however, is the fact that the majority of airlines found relevant barriers to impose restrictions within the context of a revenue management's fare structure. It is argued that, on account of the route being notably characterised by business-related trips, there is a perception that passengers may have strong disutility to such impositions, constituting a relevant competitive disadvantage. For example, the dominant airline on the route, Varig, a traditional revenue management player on many other domestic and international routes, has ever been reluctant to adopt the strategy in this specific, and quite important, market.

The difficulties related to revenue management implementation on the route led to the situation of poor financial performance in this market, contrary to common sense about that strategy. This was confirmed by the observed decrease in the average yield of the route in 1998 when compared with 1997 (R$0.309 versus R$0.390 per pax-km). It may suggest that revenue dilution was really present and was surely generated by inefficiently designed fare structures (inadequate 'fences'). Besides that, it can also mean that revenue management may not constitute dominant rationality in the market — that is, it is more profitable than uniform pricing only for a subset of airlines and not for the entire market, contrary to what was suggested by Belobaba and Wilson (1997). The present paper intends to provide support for both arguments.

Finally, it is important to make clear some of the main concepts used above.

Table 1: Price dispersion on the Rio de Janeiro–São Paulo route (current US$)

Year	*Liberalisation period*	*Full fare (Y)*	*Maximum discount fare*	*Maximum discount (%)*
1997	End of first phase	145.2	–	–
1998	Second phase	138.9	57.1	–59
2001	Second phase	119.4	56.3	–53
2002	Deregulation	133.6	46.9	–65

This section has presented a broader definition of revenue management (as in Botimer, 1996). Typically, however, the term 'revenue management' refers only to the control of reservations with seat allocations and booking limits. In this sense, it would cause confusion to compare revenue management with uniform pricing unless the latter is defined as a 'lack of both differential pricing and seat-inventory control'. By defining in this way, the remainder of the paper considers implicit the association of 'uniform pricing' with the 'first come, first served' policy.[3] The result is that the comparisons between strategies made here use two extreme situations: revenue management (multi-fare structure with booking control) versus complete absence of revenue management elements (uniform pricing, no booking control). The term 'uniform pricing' will henceforth be used to represent the latter.

THE SIMULATION OF THE RIO DE JANEIRO–SÃO PAULO ROUTE

Modelling: Entities, life cycles and consumer choice

In order to provide a competition model for the Rio de Janeiro–São Paulo route, considering all components of revenue management described in the previous section, this paper follows Belobaba and Wilson (1997) and uses a computer simulation approach.

The simulation developed has three basic characteristics: it is dynamic, as 'the passage of time plays a crucial role' (Banks, 1998); it is a discrete-event simulation model, that is, 'one in which the state variables change only at those discrete points in time at which events occur' (Banks, 1998); and it is stochastic, that is, 'one whose behaviour cannot be entirely predicted, although some statement may be made about how likely certain events are to occur' (Pidd, 1998).

Table 2 presents the main characteristics (parameters) of the simulation. It was programmed in Visual Basic and the stream of random numbers used was the same as the simulation language SIMAN (on seeds and parameters see Law and Kelton, 2000). Model variables are in Table 3.

The following subsections give details on the two most important steps of the modelling: the definition of the entities of the model and their interaction and the definition of the algorithms of passengers' rationality, respectively.

The entities of the model and their interaction

The modelling required the definition of the main features of the system to be represented (the airline market) and, especially, the description of the role of each of its entities. One important tool to 'allow the modeller to map out the main interactions and principal behaviour of the entities in a system that is to be modelled using discrete simulation' is the activity cycle diagram (Pidd, 1998). By using the activity cycle diagram (Figure 1), it is possible to show the life cycle of each class of entity and to display their relation graphically.

Basically, there are two classes of entity in the model: the passengers (temporary entities, created to enter and exit the model during the run) and the airlines (permanent entities). It is the interaction of these elements of demand and supply that permits market virtual observation and the collection of results.

Passengers' life cycle is described by some crucial events: the first one is the probabilistic arrival of demand in the airlines' reservation systems. This step requires the generation of entities and the definition of their attributes (variables in Table 3).

Following the arrival, the next event is the ordinal classification of preferences, which means that each entity will be able to classify the flights available in degrees of

Table 2: Parameters of the model

Passengers	
Average number of passenger per day	3,387
Number of passengers for the experiments (demand generation model)	Pax = 682.09 – 2.882 AverageFare + 0.451 SeatsAvailable – 105.056 DummyRecession90 + Residuals (which implies a price-elasticity of demand equal to –0.46)
Arrival of passengers (reservations) across time	Non-homogeneous Poisson Process, as in Weatherford, *et al* (1993). Intensity Function: $\lambda(t) = 3.3137 + \exp(-10.308 + 0.495\ t)$, $t = \{1, 2, ..., 30\}$
Segmentation	four segments of demand, according to the typology of Belobaba (1998): S_{01}: insensitive to price and sensitive to time; S_{11}: sensitive to price and to time; S_{10}: sensitive to price and insensitive to time; S_{00}: insensitive to price and time
Frequent Flyer status distribution	Probabilities estimated by the field research: P[FFStatus = 1] = { 0.679 for S_{01}; 0.370 for S_{11}; 0.368 for S_{10}; 0.625 for S_{00}}
Cognitive status	Full knowledge of prices and schedules of all airlines; no bounded rationality in the choice model
Number of passengers by segment	Intensity functions by segment of passengers (used to provide a proportion of segment arrivals across time): S_{01}: $l(t) = 0.0943 + \exp(-3.2011 + 0.5447\ t)$ S_{11}: $l(t) = -0.1964 + \exp(-2.7237 + 0.4425\ t)$ S_{10}: $l(t) = 0.1299 + \exp(-3.9367 + 0.5527\ t)$ S_{00}: $l(t) = 0.1800 + \exp(-12.1207 + 0.9374\ t)$
Airlines	
Relevant market	Single-leg represented by the airport-pair Congonhas (São Paulo) – Santos Dumont (Rio de Janeiro); both centrally located in the cities; majority of travelers with business purposes
Number of airlines	5: *TAM*, Varig (*VRG*), Rio-Sul (*RSL*), Transbrasil (*TBA*) and Vasp (*VSP*)
Number of code-share agreements	2: {*VRG*/*RSL*, *VSP*/*TBA*}
Number of effective players	3: {A_1 = TAM, A_2 = *VRG*/*RSL*, A_3 = *VSP*/*TBA*}
Fare structure	up to five different fare products for each airline (as in September, 1998): A_1: {full fare, –17%, –34%}; A_2: {full fare, –14%, –28%, –35%, –42%}; A_3: {full fare}
Price discrimination	Second degree (self selection)
Seat-inventory control algorithm	The extension of the Littlewood's rule made by Belobaba (1987)
Learning process	Agents need a 'warm up' period to build their demand database; the learning process does not affect the decision process in the consequent game, as the convergence to a maximization rule is fast
Fare restrictions	Availability, purchase in advance (lack of other relevant revenue management restrictions)
Flight schedule	The actual schedule as it was in 15th August, 1998, on the airport-pair Santos Dumont (Rio de Janeiro) – Congonhas (São Paulo)
Aircraft type and size	Boeing 737–300 (132 seats) and Fokker–100 (108 seats)
Diversion	Present: passengers with low sensitivity to price are allowed to buy lower prices, depending on the availability
Overbooking; cancellations; no-show; airport competition; hub structure	Absent: potential extension to the model

Table 3: Model variables

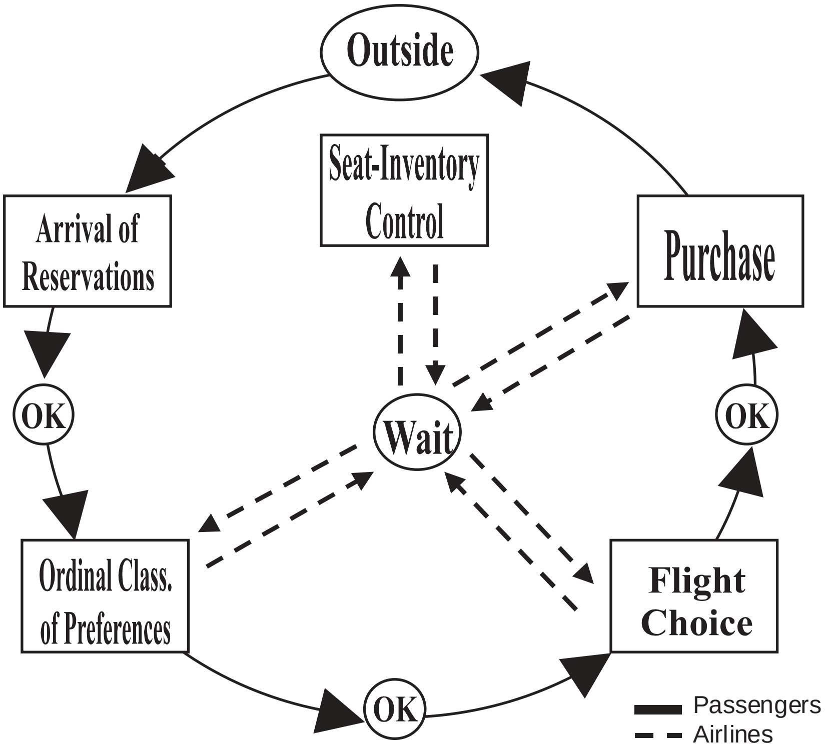
Passenger	
MySegment	The segment of demand of the passenger generated [1 if S_{01}, 2 if S_{11}, 3 if S_{10}, and 4 if S_{00}]
MyFFStatus	Frequent flyer attribute of the passenger [1 if true, and 0 if false]
MyDesiredTime	Passenger's desired time of departure
MyPreferredAirline	Passenger's preferred airline in case MyFFStatus = 1
MyFlightTable [*n*]	Set of *n* flights with departure times close to MyDesiredTime; *n* is the size of the table and it varies depending on MySegment
MyAirline	Airline chosen
MyPrice	Fare obtained by the passenger
MyFlightTime	Departure time of the chosen flight
MyScheduleDelay	[= MyDesiredTime – MyFlightTime]
Airline	
FlightSchedule	The entire schedule of flights offered on the route
RMFlightSchedule	Schedule of airlines using revenue management
FullFlightStatus	Full flight attribute [1 if full, and thus the flight is unavailable for new reservation requests, and 0 if not full]
FullFlightsTable	List of all full flights
FlightsAvailableTable	Set of all flights excluding those with FullFlightStatus = 1; this table provides the basis for the generation of MyFlightTable
FareProducts	The fare structure for each airline
AircraftSize	Size of the aircraft for each scheduled flight
SeatAvailabilityStatus	[1 if available, 0 if not available]
SeatsSold	Number of seats with SeatAvailabilityStatus = 1 in each scheduled flight
FareProductOpenStatus	[1 if open, 0 if not open]
FareProductNSeats	Number of seats allocated for each fare product in each flight
EMSR	Expected Marginal Seat Revenue (Belobaba, 1987)

preference and to choose that with the highest one, according to individual tastes and factors of choice given. For this to happen, there must be an interaction of entities in order to make passengers prompt to analyse each flight' attributes of in the available schedule.

The third event is the flight choice, another interaction of transitory and permanent entities. At this stage, reservation requests can be accepted or refused, depending on seat availability in the flight chosen. If the request is refused by the airline, a routine enables the entity to make its choice unfeasible, and then it will choose the second best option. This process continues in a loop until the request is finally accepted.

After the reservation request is accepted, the airline makes the respective seat unavailable for future consumers. It is then followed by the purchase of the ticket and the generation of revenue to the firm (third interaction, as in Figure 1). This completes the life cycle of the passenger, which is sent outside the simulation.

Figure 1: Activity cycle diagram of the airline market



Intermittently during the simulation run, airlines that practice revenue management have to promote the updating of their systems by using new information on the recent arrivals of passengers. At these moments, the simulation makes the permanent entities change from the status of inactive to active, in order for them to promote routines of seat-inventory control, one of the components of revenue management (this is done without interaction between entities). The algorithm used was the expected seat-marginal revenue (EMSR, an extension of the Littlewood's rule, as in Belobaba, 1987).

The pseudo code of the application, containing the routines created for the ordinal classification of preferences, flight choice and seat-inventory control, can be found in the Appendix.

Demand segmentation and the rationality of segments

This paper uses the demand segmentation proposed by Belobaba (1998), with four types of travellers: those with high sensitivity to time and low sensitivity to price (S_{01}), high sensitivity to time and to price (S_{11}), low sensitivity to time and high sensitivity to price (S_{10}), and low sensitivity to time and to price (S_{00}). This paper extends this framework by also considering strong airline preference (due to frequent flyer programmes, tradition, in-flight amenities, perceived comfort, etc. Data on both segmentation and strong preference were collected by a field research at the Airport of São Paulo (CGH), and details can be found in Oliveira (2000).

Basically, there were three algorithms of flight choice for each demand segment.

The first algorithm was the one assigned to segment S_{01} (passengers with high sensitivity to time and low sensitivity to price). As the price of the airline k in the flight j, p_j^k, has either low or no influence on the choice behaviour of this segment, its ordinal classification of preferences was then designed to be based on the schedule delay, Sd.[5] The more the schedule is delayed, the more is this segment of demand's disutility, and thus its choice was based on the criterion of minimisation of that variable.

The second algorithm used was defined for the segments with higher sensitivity to price (S_{11} and S_{10}). In those cases, the ordinal classification used a table of flights — a list of flight times with the lowest schedule delay (the closest to the desired departure time). Once the table is generated, there is an additional ordinal classification based on price minimisation, which means that the choice of those segments targets the best price among the flights with the lowest schedule delay. The difference between S_{11} and S_{10} is the size of the table, that is, the number of flight times with the lowest schedule delay considered in order to make the price ordinal classification — which is higher in the latter segment.

Finally, the third algorithm used was assigned to the segment S_{00}. As the field research (Oliveira, 2000) concluded that this segment has very reduced participation in the market, there was a problem of inference about its behaviour. In this case, the best standard of choice defined was to create another table of flight times, and then to randomise its choice within it. Under circumstances of uncertainty of behaviour, the uniform distribution was preferred as a proxy.

Undoubtedly, other criteria of choice could be used in order to develop the algorithms to deal with the rationality of passengers' choice — this represents an advantage of computer simulation, as it can experiment with many patterns of possible behaviour. For the present application, however, the algorithms described above were considered efficient in terms of the tests of hypotheses, validation and market reproduction.

Calibration and validation of the model

The step of calibration involved the feeding of the simulation model with input data. There were two main groups of inputs: demand data (total passengers, total passengers across time, total passengers across a day and passenger segmentation) and supply data (airline schedule, size of aircraft, fare products and algorithm of seat-inventory control). The main sources for both groups were the yearbooks of the Department of Civil Aviation, the airlines and field research performed in January 2000 at the departure lounges of the Airport of São Paulo (CGH).

This study has developed a sequential sample size estimator in order to promote the validation of the simulation model, as suggested by Kleijnen (1975) and Law and Kelton (2000). The basic idea of this process of validation is to promote student t tests for the sample average of the output variables, building confidence intervals, given a significance level of α. Thus, it is designed a number n $\{n = n_0, n_0 + 1, ...\}$ of model replications, increasing in one the number of runs until the sample variance is satisfactorily low — which is controlled by comparing the calculated interval $\theta(n,\alpha)$ around the average, with a desired interval θ_d, previously determined:

$$\theta_d \geq \theta(n, \alpha) = t_{n-1,1-\alpha} S_X / \sqrt{n} \qquad (1)$$

where θ_d is the desired precision (interval), $t_{n-1,1-\alpha}$ is the student t value and S_X is the sample variance of the output variable X. As soon as condition (1) is satisfied, the number n of replications designed, $n^\star(\theta,\alpha)$, is the sample size that determines, with a level of significance α, one estimate of sample average with a confidence interval less than a desired precision. In the case where the average of the variable collected in the system is within the upper and lower limits of the intervals, the model is considered validated by this criterion, that is, the hypotheses tested do not reject the null hypothesis that the simulation model adequately represents the real system.

Law and Kelton (2000) recommend the use of n_0 equal or higher than ten, and a maximum value of θ_d of 15 per cent of the sample average: these rules are followed by the present paper.

The model validation and tests were conducted by the use of market share as the output variable. Thus, a simulation scenario was built exclusively aiming validation, and used actual 1997 input data (SC_{97}); this step was then followed by the collection of simulated market share data and a comparison with the 1997 figures (Table 4).

Finally, the model was considered validated, given α equal to 0.10, and θ_d equal to 0.50 per cent. The total number of replications required was $n^{\star}(\theta,\alpha) = 15$. It is possible to observe that all values in column (5) of Table 4 (actual market shares in 1997) are within the confidence interval developed (market share lower and upper limits), as required by this specific form of validation procedure.

EXPERIMENTATION: AN ASSESSMENT OF REVENUE MANAGEMENT IN THE MARKET

The previous section described how the scenario SC_{97} was built and validated. Once this phase was concluded, one advantage permitted by the simulation was to perform some convenient experimentation with the elements of the model, in order to infer the effects and sensitivity of them to the output variables.

Thus, the main exercise of experimentation here was to insert the set of components that form the revenue management, as SC_{97} had only 'first come, first served', uniform pricing characteristics.[6] This allowed the assessment of revenue management's impacts in the economic efficiency of the market and also some inferences on its rationality as a strategy in the market.

The model was then replicated the number of times necessary to make it statistically significant, and the following output variables were collected: quantity of passengers per airline (Qd_k), market share in quantities (MS_k^{qd}), total revenues yielded (TR_k), market share in revenues (MS_k^{TR}), average revenue yielded (AR_k), profits (π_k), load factor by airline (LF_k), and average price and average schedule delay by each segment of passenger (P_i and Sd_i); this procedure was implemented for each experimental scenario.

Table 4: Results of model validation — scenario SC_{97} (%)

	(1)	(2)	(3)	(4)		Confidence interval		(5)
Airline	*Simulated market share MS*	*Variance $S^2[MS]$*	*Calculated θ ($n = 15$; $\alpha = 5\%$)*	*Desired θ d*	*(3)/(1)*	*MS lower limit*	*MS upper limit*	*Actual market share (97)*
VRG	40.6	0.29	0.19	0.50	1.23	40.1	41.1	40.1
VSP	24.4	0.56	0.36	0.50	2.05	23.9	24.9	24.5
TBA	16.0	0.36	0.23	0.50	3.13	15.5	16.5	15.9
RSL	6.5	0.32	0.21	0.50	7.68	6.0	7.0	6.7
TAM	12.5	0.27	0.17	0.50	4.02	11.9	12.9	12.8

The following sections report two main steps of the experimentation:

(1) assessment of impacts in market efficiency, by the development of two scenarios: SC_{RM}, in which the airlines used revenue management in the same condition that was done in 1998; and SC_{UP}, in which the airlines used uniform pricing, in the same condition prior to the introduction of revenue management;
(2) analysis of revenue management rationality, by the development of six additional scenarios, which could represent possible 'strategic moves' by the airlines (investigation into the strategic interaction of the airlines).

In fact, the first step represents the main goal of the present computer simulation, while the second one is an extension to the model — an articulation of a simulation with an analytic model, demonstrating that they can be complementary in economic analysis, and not only substitutes.[7]

Analysis of the impacts in market efficiency

In order to assess the impacts on economic efficiency caused by revenue management on the route, scenario SC_{RM} was created. In this scenario, airlines have a fare product structure along with a booking control algorithm, whereas in scenario SC_{UP} they use a 'first come, first served' with uniform pricing policy. It is important to emphasise that both scenarios were set with the values and standards effectively used in the market.[8]

Tables 5 and 6 present a comparison between results of simulated scenarios SC_{UP} and SC_{RM}. Results were disaggregated by segment of consumer (S_{01}, S_{11}, S_{10} and S_{00}) and by group of airlines that had code share agreements in 1998. Four criteria were considered: average prices (disbursement), schedule delay, profits and passengers carried:

It can be observed that the decrease in the average price charged to the segments of passengers and to the demand in general (Criterion 1) was concomitant with the decrease in the profits of the three groups of airlines (Criterion 3). Indeed, all the groups of airlines had relevant profit losses of at least 14 per cent, due to lower revenue.[9]

This aspect of poor financial performance in the supply side, observed in the scenario SC_{RM}, has the least justification: the effects of the 'weak', inadequate product differentiation. Revenue management is a known instrument of revenue optimisation, which undoubtedly increases the chances for profits to increase.[10] If there is imperfect demand segmentation (meaning product differentiation inefficacy), however, the tendency is for the to gain in profitability to be reduced by revenue dilution.[11] Without an efficient introduction of purchase restrictions ('fences'), not only based on the advance in the reservation and flight time — as in this case — the scheme of second degree price discrimination with self-selection can be ruined. This phenomenon tends to be worse on routes such as Rio de Janeiro–São Paulo, in which there are not many advance reservations.

Thus, dilution in revenue was the main problem found in scenario SC_{RM}, as well as in all scenarios where revenue management was present. Table 7 illustrates this point by presenting the diversion of segment S_{01} to discount fares, which accounted for up to 24 per cent of total revenues.[12]

Another quite relevant issue to consider normatively is the increase in passengers carried (criterion 4 of Table 6). This is especially important because air transport is not as popular mode of transportation in Brazil as it is in other countries, owing to low average income and relative prices of the alternatives.

The final point is the analysis of the efficiency in allocation (Botimer, 1996) as a

Table 5: Summary of results of the scenarios SC_{UP} and SC_{RM} (demand)

Criterion 1: Disbursement (Avg. Price)	*Scenario of Unif. Pricing (SC_{UP})*	*Scenario of Rev.Managmt. (SC_{RM})*	*SC_{RM}–SC_{UP} (%)*
Segment S_1	115.4	109.9	–5
Segment S_2	115.3	95.5	–17
Segment S_3	115.1	94.8	–18
Segment S_4	115.5	106.2	–8
Demand in 1998 R$	**115.4**	**107.1**	**–7**
Criterion 2: Schedule delay	*Scenario of Unif. Pricing (SC_{UP})*	*Scenario of Rev.Managmt. (SC_{RM})*	*SC_{RM}–SC_{UP} (%)*
Segment S_1	1:16	1:13	–4
Segment S_2	0:47	1:49	+130
Segment S_3	1:06	1:54	+72
Segment S_4	5:31	5:21	–1
Demand in hours	**1:17**	**1:24**	**+10%**

Table 6: Summary of results of the scenarios SC_{UP} and SC_{RM} (supply)

Criterion 3: Profits	*Scenario of Unif. Pricing (SC_{UP})*	*Scenario of Rev.Managmt. (SC_{RM})*	*SC_{RM}–SC_{UP} (%)*
A_1: TAM	1.5	0.8	–46
A_2:VSP– TBA	18.1	14.5	–20
A_3: VRG – RSL	13.5	11.6	–14
Supply in 1998 R$ (million)	**33.1**	**26.8**	**–19**
Criterion 4: Seats sold	*Scenario of Unif. Pricing (SC_{UP})*	*Scenario of Rev.Managmt. (SC_{RM})*	*SC_{RM}–SC_{UP} (%)*
A_1: TAM	96.6	99.6	+3
A_2: VSP – TBA	475.3	513.7	+8
A_3: VRG – RSL	508.0	491.0	–3
Supply (in thousands of seats)	**1,079.9**	**1,104.4**	**+2**

Table 7: Distribution of diversion to discount fares (segment S_{01})

Airline	*Total non-diverted (Full fare)*	*Diversion to deep discounts (30–50%)*	*Diversion to moderate discounts (< 30%)*	*Total diversion in % of revenues*
$A_1(SC_4)$	77	5	18	23
$A_2(SC_2)$	76	10	14	24
$A_3(SC_1)$	82	7	11	18

second best for the market welfare. Revenue management generated an allocation of the service in a more adequate way for the consumers who value it the most. Criteria 1 and 2 permit observation of this effect in a proper way: thus, to the segment of consumers S_{01} — the most representative on the route — which is more sensitive to time, there was allocation of flights at times closer to their desired time of departure (schedule delay reduction, criterion 2), which certainly increased their welfare. What is more, lower-priced flights (criterion 1) were allocated to the segment of consumers S_{10} more sensitive to prices, which also contributed to the increase in their welfare. Both gains represented increases in general efficiency in allocation of the market.

The conclusion is that revenue management on the Rio de Janeiro–São Paulo route was an important instrument of welfare generation, mainly when considering the concept of welfare in allocation (demand side). It also permitted a significant increase in the average load factor (supply side). The strategy had negative impacts, however, in relation to relevant variables such as revenues and profits. On account of that, it can be concluded that the correction of problems related to revenue dilution should be stimulated by the airlines and by the authorities in charge of the industry.

In order for revenue management to have its positive welfare impact optimised, there must be an effective reinforcement of its three basic components. Thus, there must be the promotion of better-designed price discrimination schemes, higher investment in more sophisticated systems of seat-inventory control, and, last but not least, a more adequate use of product differentiation, by the imposition of better mechanisms of segmentation — purchase restriction or 'fences' — in order to avoid the phenomenon of revenue dilution.

Analysis of airline strategic interaction

A final issue addressed by the simulation model was the investigation into the rationality of the airlines in relation to revenue management. The section on 'The entities of the model and their interaction' described the rationality of demand agents (segments of passengers) through the development of algorithms of choice. With regard to the airlines, the element of rationality considered was the revenue-maximisation target, as permitted by the routines of seat-inventory control. In fact, a learning process was permitted in order for airlines to build their demand database, and thus to achieve that target (Table 2); however, the convergence to the maximisation rule was fast enough for the strategic decisions to be affected.

A problem not explained so far, however, was the motives of actual revenue management utilisation on a route like that, with characteristics of 'shuttle service markets' — high inelasticity to price of demand and low advance reservations. Is there a dominant rationality, that is, in all possible competitive cases has the strategy of revenue management an advantage over its alternatives (eg Belobaba and Wilson, 1997; Smith *et al.*, 1992)? And what about uniform pricing?[13] Are there cases in which, depending on the competitive conditions, it can be more advantageous than revenue management?

In order to answer these questions, a relevant characteristic of computer simulation models was implemented: the possibility of articulation with analytic models. With the purpose of demonstrating this potential of complementarity between both kinds of approach, the present paper developed some experimental scenarios in order to feed an analytic model — a game theoretical model of the competition on the route, called 'the revenue management game'.

By using three players (A_1, TAM; A_2, VSP-TBA; and A_3, VRG-RSL) and two strategies (either to play uniform pricing, UP, or revenue management, RM), 2^3 experimental scenarios were needed. Two of them have already been developed in the section on 'Analysis of the impacts in market efficiency'. Six additional scenarios, presenting other possible strategic subsets for the airlines, were then built. Table 8 presents the scenarios developed.

Suppose that after the liberalisation of the beginning of 1998, the problem of analysis of the airlines' rationality could then be posed as a simultaneous non-cooperative game (as in Figure 2). The pay-offs of the players (airlines) in the game are disposed under the terminal nodes of the tree diagram and represent the results of each scenario simulated; they are expressed in terms of an index of profits π_k, $k=1, 2, 3$ (π_2 in SC_{UP} equal to 100).

The solution of the game can be obtained by Backward Induction,[14] presented by Equation 2. σ_{A1}, σ_{A2}, and σ_{A3} are the strategic profiles of the solution[15] for each player:

$$\begin{bmatrix} \sigma_{A1} \\ \sigma_{A2} \\ \sigma_{A3} \end{bmatrix} = \begin{bmatrix} RM \\ UP, \quad \forall \sigma_{A1} \\ UP, \quad \forall \sigma_{A1}, \sigma_{A2} \end{bmatrix} \qquad (2)$$

The results in (2) make clear that revenue management is dominant (that is, played independently of the other players' moves) only for A_1, but not for the remaining airlines, for which uniform pricing is dominant. Thus, solution (2) leads to the conclusion that RM is not globally advantageous and that it depends on the competitive conditions and revenue capabilities to be better than the traditional practice of uniform pricing. These results contrast to the ones achieved by the simulation of Belobaba and Wilson (1997), where 'effective yield management results in revenue increases for the users of YM in virtually all competitive situations'.

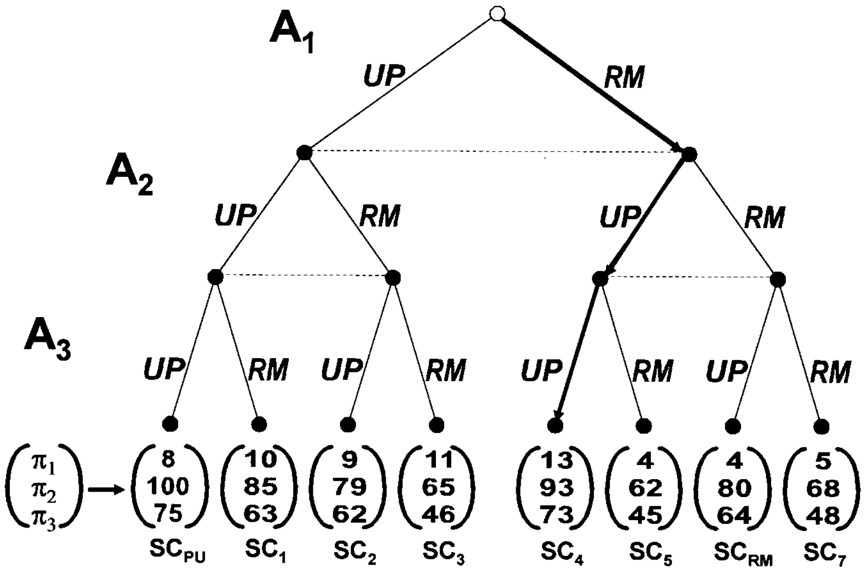
One important issue to emphasise, however, is that (2) was built based on the development of the simulation model in

Table 8: Experimental scenarios designed in the simulation

Scen.	*Description*	*Scen.*	*Description*
SC_{UP}	The three players play UP (Mar/98)	SC_{RM}	A_1, A_2 play RM whereas A_3 plays UP (Sep/98)
SC_1	A_1, A_2 play UP whereas A_3 plays RM	SC_4	A_1 plays RM whereas A_2, A_3 play UP
SC_2	A_1, A_3 play UP whereas A_2 plays RM	SC_5	A_1, A_3 play RM whereas A_2 plays UP
SC_3	A_1 plays UP whereas A_2, A_3 play RM	SC_6	The three players play RM

A_1: Player 1 (TAM); A_2: Player 2 (VSP–TBA); A_3: Player 3 (VRG–RSL); UP: uniform pricing; RM: revenue management.

Figure 2: The revenue management game



the same way as was performed on the route, that is, using a 'weak' product differentiation scheme (inefficient purchase restrictions). Even disregarding the 'dilution effect', however, the results clearly indicated that revenue management was only locally advantageous and permitted profit gains to only a subset of airlines.[16] The Rio de Janeiro–São Paulo route was then considered a fine case study of a market less sensitive to price and with homogeneous patterns of demand arrivals in reservation systems, which may roughly explain the poor financial performance recently observed, even under the presence of a strategy supposed to enhance the firm's profits in most of the situations.

Another relevant difficulty in comparing the present approach with that of Belobaba and Wilson (1997) is that they do not adopt uniform pricing as firms' alternative to revenue management. Their 'no yield management' situation means 'no seat-inventory control in a multi-fare pricing structure'. Here 'uniform pricing' is considered as one extreme alternative to revenue management, as explained in the last paragraph of the first section.

CONCLUSIONS

This study has developed a computer simulation model to analyse the impacts of revenue management in a recently liberalised airline industry, Brazil, focusing on its most important route, Rio de Janeiro–São Paulo. This is a business market widely recognised as having a highly price-inelastic demand. For that purpose, it used real data for model calibration, and performed a process of validation — a different methodology from the hypothetical markets of Belobaba and Wilson (1997).

The conclusions are that revenue management had positive impacts in terms of efficiency in allocation, that is, in 'ensuring that a scarce resource is provided to the members of the population who intrinsically value it most' (Botimer, 1996). Thus, to the segments of passengers with highly time-sensitive demand (and therefore with higher reservation prices) seats were allocated closer to their desired time of departure. Moreover, to the highly price-sensitive segment, it permitted allocation of seats with lower prices. In both cases, the welfare of passengers was increased. On the supply side, there was an overall increase in load factors in the market.

In spite of these positive aspects, much revenue dilution was observed on the route, caused by inadequate purchase restrictions ('fences', which are fundamental elements of product differentiation necessary for the revenue management to be effective). In fact, the airlines in the market only implemented restrictions of advance purchase and flight time availability. This certainly was the cause of much revenue loss in a route characterised as a 'shuttle service market' — low rates of arrivals in advance on account of the high service levels.[17] Hence, this paper highly recommends the introduction of more adequate elements of fare restriction in order to correct 'weak' product differentiation and to enhance revenue management capabilities.

Another relevant aspect of the modelling is that uniform and differential pricing used here were precisely the same as observed in practice. This led to the definition of a uniform fare equal to the undiscounted fare in the differential pricing scheme, as adopted by airlines on the route. This could represent a potential underestimation of revenue generation by the latter,[18] especially because previous studies of differential pricing have assumed multiple fares involving both lower and higher fares than the single uniform pricing strategy. In the end, however, the comparison between strategies permitted by the model could reproduce the same competitive dilemma on the route.

One additional objective of this paper was the analysis of airline rationality in introducing revenue management. This was motivated by the fact that some of them preferred to maintain uniform pricing (and so, to have a 'first come, first served' policy), and not to react. By using an articulation of experimental scenarios and a game theoretical model, it was possible to indicate that revenue management was not really a dominant and/or a stable strategy for some of the players.

The final conclusion is about the methodology of computer simulation as an alternative to more usual analytical models of competition. It permitted the development of crucial details in the modelling of the agents in the market, mainly on the issue of the rationality of the passengers. It also permitted the consideration of relevant characteristics of the airline market, such as probabilistic arrival of reservations, demand segmentation, capacity optimisation algorithms and price discrimination, which would be complex to treat simultaneously in any analytical model. Thus it was considered satisfactory, as it allowed the better understanding of the decision-making process and firms' rationality, as well as permitting the design of experiments for the analysis of competition in airline markets.

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NOTES

1 Considering the period of 1997–1998 (yearbook of the Department of Civil Aviation).

2 A complete survey of revenue management literature can be found in McGill and Van Ryzin (1999).

3 FCFS is the situation where the airline accepts 'any and all booking requests until the total capacity of the flight leg is reached' (Belobaba and Wilson, 1997).

4 In that field research, 402 questionnaires were collected from the passengers at the airport.

5 The delay, measured in time units, that the

flight departure time represents in relation to the passenger desired departure time.

6 Revenue management was introduced only in 1998 on the Rio de Janeiro–Sao Paulo route.

7 This paper then follows the suggestion of Judd (1997).

8 As described in Table 2.

9 It is important to emphasise, however, that SC_{RM} is not the scenario where *all* airlines use revenue management. As can be seen in Table 2, in this scenario only A_1 and A_2 uses the strategy (as in September, 1998). This does not change the results because scenario SC_6 in Table 8, in which all airlines have revenue management, also contains the characteristic of generalised financial performance.

10 Check, for example, Belobaba (1987), Belobaba (1989) and McGill and Van Ryzin (1999).

11 As emphasised by Oliveira and Serapião (2001) in a study of the Brazilian market.

12 SC_1, SC_2, SC_4, and all other experimental scenarios are described in the next section.

13 Remember that uniform pricing was defined in the last paragraph of the first section as the antithesis of revenue management.

14 For the definition of this concept, check Mas-Colell *et al.* (1995).

15 That is, the SPNE (Subgame perfect Nash equilibrium).

16 The figures of the scenarios disregarding revenue dilution can be found in Oliveira (2000).

17 This was observed for all demand segments.

18 Which could be worse if we take into account the low price-elasticity of demand (see demand estimation in Table 2).

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APPENDIX: SIMULATION PSEUDO CODE

Figure A1: Pseudo code of ordinal classification of preferences and flight choice

Procedure [Ordinal Classification of Preferences and FlightChoice]	
Begin	
Repeat until no more passengers	
Read Passenger (MySegment, MyDesiredTime, MyFFStatus, MyPreferredAirline)	' collect demand attributes;
FlightsAvailableTable = FlightSchedule - FullFlightsTable	' exclude full flights;
If MyFFStatus = 1 MyFlightTable = MyFlightTable - Airlines different from MyPreferredAirline Endif	' exclude other airlines if it is a frequent flyer;
Calculate MyScheduleDelay Sort MyFlightTable (MyScheduleDelay; Descending)	' classify all flights in terms of schedule delay in relation to the variable MyDesired Time (ordinal classification of preferences for S_{01});
Switch PassengerSegment	
Case S_{11}: MyFlightTable = MyFlightTable - All flights with MyScheduleDelay > than the first 5 least Sort MyFlightTable (Price; Descending)	' ordinal classification of preferences for S_{11};
Case S_{10}: MyFlightTable = MyFlightTable - All flights with MyScheduleDelay > than the first 3 least Sort MyFlightTable (Price; Descending)	' ordinal classification of preferences for S_{10};
Case S_{00}: MyFlightTable = MyFlightTable - All flights with $\text{MyScheduleDelay}_{ij}$ > than the first 10 least Assign random number ~U(1,10) to each flight Sort MyFlightTable (U; Descending)	' ordinal classification of preferences for S_{00};
Endcase	
MyFlight = The first in MyFlightTable	' generate the flight choice;
SeatAvailabilityStatus = 1	' register passenger's choice;
If Flight is Full FullFlightStatus = 1 Endif	' check if flight is now full;

Figure A2: Pseudo code of seat-inventory control

```
Procedure [Seat-Inventory Control]

Begin

    RMFlightSchedule = FlightSchedule - FullFlightsTable - Flights    ' exclude full flights and
    Airlines with Uniform Pricing                                      uniform price flights;

    Suspend passengers arrivals in the reservation

    Repeat until no more flights in the RMFlightSchedule

        Read Flight (FareProductOpenStatus, SeatsAvailable)            ' collect data from the
                                                                       reservation system
                                                                       (update seat-inventory
                                                                       control system with
                                                                       recent arrivals);

        Repeat until no more FareProducts in the Flight

            Calculate Averg [SeatSold], Var [SeatSold], EMSR           ' apply the EMSR
            Generate FareProductNSeats                                 Rule for each fare
                                                                       product available in
                                                                       each flight

        Next FareProducts

    Next Flight

End
```