A NORMATIVE SIMULATION FOR AIRLINE MARKETING PLANNING

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ABSTRACT

This paper reports on the development of a heuristic aid to making marketing planning decisions that is data based and explicitly considers the uncertainty of competitive behavior. An application of the model to an airline market provides conclusions about the nature of the market and how to assess competitive response. Normative simulation appears to have good potential as a decision-making aid for marketing managers.

I. BACKGROUND

The use of simulation falls into three general areas of application: research, instruction, and decision-making [2]. Research and instructional uses of simulation are most common, ranging from simulations that serve as vehicles for theory building to simulations that are designed as teaching or training devices Simulation's use as an aid to decision-making, however, is less developed despite its attractiveness as a method for structuring problems (i.e., modeling decision situations) and exploring optimal solutions to them. The domain of problems to which this use of simulation can be applied includes not only problems of business firms but also problems of non-business organizations and public agencies. This paper demonstrates how simulation can be useful to aid marketing managers in solving the marketing mix planning problem in an airline setting. The extension of this work to other decision situations can lead to greater realization of the potential of normative simulation.

The Airline Marketing Mix Planning Problem

An airline's marketing mix, or set of marketing decision (control) variables, includes flight scheduling, advertising, and other promotional efforts. The two primary influences on an airline's market share in a city-pair market for passenger travel have been found to be number of flights and dollars of advertising [4]. The airline marketing mix planning problem concerns how to adjust these variables over time so as to maximize some objective, say city-pair profit. Airlines currently deal with this problem by relying on decision heuristics and rules-of-thumb, but these informal procedures do not provide a rigorous means for controlling the situation. One of the most interesting aspects of the problem is how to assess the nature of competitive response to the airline's own marketing actions. Thus, the planning problem involves four major steps: (1) forecasting total market demand, (2) planning the marketing mix, (3) estimating the reactions of competition, and (4) forecasting company sales or market share and profit.

This paper focuses on the third step: predicting the effects of competitive behavior. We assume here that the airline has acceptable models for forecasting total market demand and market share and use empirical results from previous research [3]. We also assume that the airline has estimated linear decision rules that its competitors may be using to make their own decisions and, again, employ empirical findings from a prior study [5]. The task, then, is to develop a normative optimization model --a simulation of competitive behavior--and (a) to determine optimal policies for the airline assuming that one decision rule is being used and do this for the set of empirical decision rules, and (b) to determine an optimal strategy for assessing competitive behavior that considers the uncertainty of competitive response.

II. THE SIMULATION

There are two major aspects to the normative simulation. First, it is a conditional optimization. The firm, airline K, makes an assumption about the decision process of its competitors, airlines L and M, and then it optimizes its number of flights as if the competition will react in one of several ways with certainty. The optimization is conditional because it depends upon whether or not the assumed competitive response actually occurs. The payoffs (in profit) to the firm thus result from some combination of assumed and actual behavior. Second, it is an optimization under uncertainty since the payoff matrix can be examined for optimal assumptions about competitive behavior. In this case, optimal assumptions are equivalent to optimal strategies since they dictate the nature of competitive interaction and consequent market performance.

Simulation Model. The simulation is built around a marketing model consisting of (1) a market share response function, (2) a firm objective function, and (3) competitive flight decision rules.

Consider the following equation chosen from empirical research [3] to represent the process generating the firm's market share behavior.

$$(1) \qquad m_{Kt} = \alpha f_{Kt} + \beta a_{K_{t-1}} + \gamma c_{K_t} + \delta$$

where:

m_{K_t} is airline K's market share in city pair R-S in period t,

f_{K_t} is airline K's frequency share of non-stop flights in period t,

$a_{K_{t-1}}$ is airline K's advertising share in city R in period t-1, and

c_{K_t} is the population share or ratio of airline K's passengers to total passengers in city R in period t.

In words, the model says that the firm's market share is related to its current frequency share, lagged advertising share in city R and to its population share in city R.

For purposes of optimization, it is necessary to express the "decision" variables explicitly. The firm sets the number of flights and the level of advertising expenditures, not flight shares and advertising shares. The "constants" can be omitted in this step since they do not affect the optimization.

$$(2) \quad m_{K_t} = \alpha \left(\frac{F_{K_t}}{F_{K_t} + F_{O_t}} \right) + \beta \left(\frac{A_{K_{t-1}}}{A_{K_{t-1}} + A_{O_{t-1}}} \right)$$

where:

$F_{O_t} = F_{L_t} + F_{M_t}$ is the competitors' number of daily non-stop flights in period t and

$A_{O_{t-1}} = A_{L_{t-1}} + A_{M_{t-1}}$ is the competitors' level of advertising expenditure in city R in period t-1.

The firm's goal is assumed to be profit maximization. Since the market share model is dynamic, the optimization must cover multiple time periods. The objective function for the firm can be written as

$$(3) \quad \pi = \sum_{t=1}^{n} \pi_t = \sum_{t=1}^{n} PR_t D_t m_{K_t} (F_{K_t}, F_{O_t}, A_{K_{t-1}}, A_{O_{t-1}}) - c\, F_{K_t} - A_{K_t}$$

where:

π_t is city-pair profit in period t,

PR_t is price in period t,

D_t is market demand in period t,

c is the cost of one flight in city pair RS per period, and

n is the planning horizon.

Differentiating equation (3) with respect to firm flights and firm advertising produces a set of homogenous equations which can be solved to determine optimal flights and advertising. The solution, however, depends upon knowledge of PR_t, D_t, F_{O_t}, and A_{O_t} for each period. Price in the industry is easily predicted since it is fixed and can only be changed with the approval of the Civil Aeronautics Board. Demand is a variable which is assumed to be outside the control of the firm. Demand, however, is related to price, seasonality, and national personal income and can be accurately predicted [3]. Competitors' flight scheduling and advertising expenditures are less easily explained or predicted.

To explain or predict competitors' flight scheduling and advertising requires knowledge of the decision rules used to set flights and advertising expenditures. On the basis of interviews with management we formed the premise that scheduling decisions are interdependent and that advertising decisions are independent. This dichotomy stems not only from the fact that flights are the primary marketing tool in airline markets, but also because scheduling is a much more "visible" marketing policy, at least in terms of measurement and expected impact. Advertising is thought to play a lesser role and certainly one where the influence is more difficult to assess. Airlines are thus more likely to compete through scheduling than advertising and so competitors are more likely to react to flight changes than advertising changes. From this basic premise, we conclude that empirical decision rules must reflect this kind of behavior to be considered in agreement with the real market.

Another premise, derived from the management interviews, is that the firms' decision rules are neither deterministic nor random. The imprecision of this premise results from management's own inability to articulate the exact decision rules employed and, more importantly, the consistency with which they are used.

After collecting and examining the data, we were able to develop a set of plausible decision rule functions for flights based on both management's view of the process and some theoretical guidelines due to Kotler [1]. Advertising decision rules are not considered in the simulation. The following set of decision rules has been suggested by Kotler and differ according to environmental factors considered, complexity of response, and objectives of the firm:

1. Non-adaptive
2. Time-dependent
3. Competitively adaptive
4. Sales responsive
5. Profit responsive
6. Completely-adaptive
7. Diagnostic
8. Adaptive profit-maximizing
9. Joint profit-maximizing.

These decision rules, when operationalized in the airline setting, provide the basis for investigating the nature of competitive behavior.

The next step was to find linear equations that approximate these decision rules. The normative planning model does not require that one rule be selected as the truth, but rather recognizes the uncertainty of competitive response and proceeds with a conditional optimization of profit based on a variety of plausible rules.

It is assumed in the simulation that the firm follows an adaptive profit-maximizing strategy. Optimal flights are calculated in response to the marketing mix moves of the firm's competitors. The first type of strategy considered is a non-adaptive strategy where the marketing mix remains unchanged throughout the planning period. This strategy is identified in the tables and in Figure 2 as (6b) (6c).[1] A time-dependent strategy adjusts a firm's marketing mix on the basis of trend, seasonality and/or past marketing mixes; decision rules (7b) (7c) adjust flights to the growth trend in the market; decision rules (8b) (8c) adjust flights to trend and seasonality; decision rules (9b) (9c) adjust flights to last period's flights; and decision rules (10b) (10c) adjust flights to last period's (quarter's) flights and last year's flights. The competitively adaptive decision rules (11b) (11c) adjust flights on the basis of competitors' flights. The use of sales responsive, profit responsive, diagnostic or joint profit-maximizing decision rules require a sales response function for the firm's competitors' and are not considered in the simulation. Completely adaptive decision rules (17b) (17c) were used which adjust flights to changes in competitors' flights and time dependent market changes.

Simulation Program. The simulation proceeds as diagrammed in Figure 1. The simulation is initialized at time t = 0. The simulation operates as if the firm would not change its goal, adaptive profit-maximization, over the 28 periods to be simulated, although the planning model only assumes a four-period (quarter) horizon. Historical advertising expenditures for the airlines are used in the simulation. Other inputs include price, demand, and population share. Thus, the only control variable for each airline is flights. Given the inputs and an estimate of competitors' flights for the next period (which comes from one of the empirical decision rules), airline K can compute the number of flights that will maximize its profit.

Now, as the flow chart shows, there may be some competitive response to this tentative "optimal" level of flights for airline K and so the simulation reestimates competitors' flights on the basis of the decision rules under consideration. If competitors' decision rules adjust flights independently of the firm's flights no competitive response occurs. If the assumed competitors' decision rules involve a competitive reaction the firm's optimal level of flights is recalculated to produce a new tentative "optimal" level of flights. When there is no further expected competitive reaction, airline K's marketing mix is set as the (conditionally) optimal number of flights and the historical dollars of advertising. The simulation then inputs airline K's marketing mix and actual competitors' marketing mixes into the firm's market share model. The output each period includes airline K's market share, unit sales, revenue, profit and load factor. The program reiterates this process over the full 28 periods, i.e., until t=N, to complete one simulation run.

The competitors' marketing mix used in the simulation consists of competitors' historical advertising expenditures and competitors' flight levels derived from empirical decision rules. Thus, the output generated for each run is based on an assumed and an actual set of decision rules for airlines L and M. Both sets of rules remain unchanged throughout a simulation run. Since there are six possible types of reasonable actual decision rules and seven possible types of assumed decision rules, the simulation is run for each possible pairing of assumed and actual rules to produce a seven by six payoff matrix which summarizes the possible results of the dynamic market process.

Simulation Results. We start the analysis with a simulation run based on historical flights. In this run no optimization takes place. Historical flights are used for airlines K, L and M. The results are shown in the first column of Table 1. "Actual" total profit for the firm, airline K, is \$51,379,060, average market share is 17.3% and the average load factor is 21.8%.

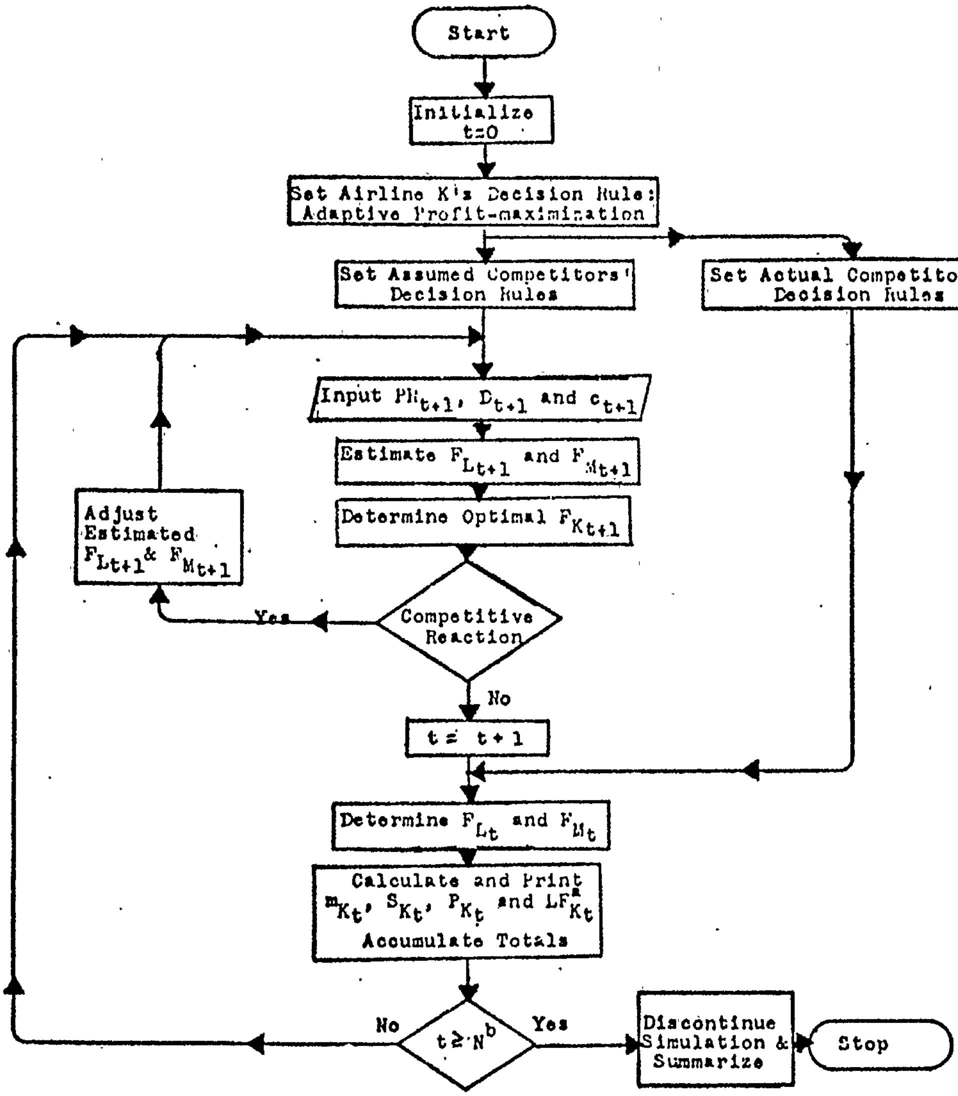
Table 1 also contains the results of runs which optimize flights for the firm based on estimates of competitors' flights from each possible type of assumed decision rule. In each of these cases the flights of competitors are from historical data. This amounts to the restrictive assumption that the implementation of optimal flights by the firm does not stimulate competitors to react or depart from historical observed behavior. The last column in Table 1 is based on an optimization with perfect predictions of competitors' flights.

An important consideration is whether or not the optimal flights implemented by the firm would stimulate a competitive reaction. It can be seen from Table 2 that the firm's optimal flights frequently depart from historical flights, sometimes by as many as eight. Such drastic adjustments to airline K's scheduling would undoubtedly create changes in market conditions which would cause competitors to react by also adjusting their flight schedules.[2]

The value of the simulation approach lies in its ability to capture the competitive reaction mechanism. Given an actual set of competitive decision rules and an assumed set of decision rules it is possible to generate a matrix of simulated market results, Table 3. Each cell of the matrix contains profit in millions of dollars, average market share in percent and average load factor in percent for the firm over the simulation run. The assumed decision rules provide estimates of competitors' flights which are input to the firm's profit-maximizing flight equation. Actual competitors' decision rules generate flight schedules which when combined with the firm's optimal flight schedule, produce the firm's market share, profit and load factor. Each simulation run produces a history of market activity which is summarized in a cell of the matrix. For example, if the firm assumes competitors are using decision rules (6b) and (6c) and calculates its optimal flights based on estimates from these equations but in fact competitors use decision rules (7b) and (7c), then the firm's simulated market profit is \$56,990,000, its average market share is 17.6% and its average load factor is 39.8%.

Figure 1

Simulation Flow Chart



[a] LF_{K_t} is airline K's load factor in period.

[b] N is the simulation period.

Figure 2

Market Profit for Airline K vs. Accuracy of Estimated Decision Rules

Simulated with Actual Competitors' Decision Rules (7b) and (7c)

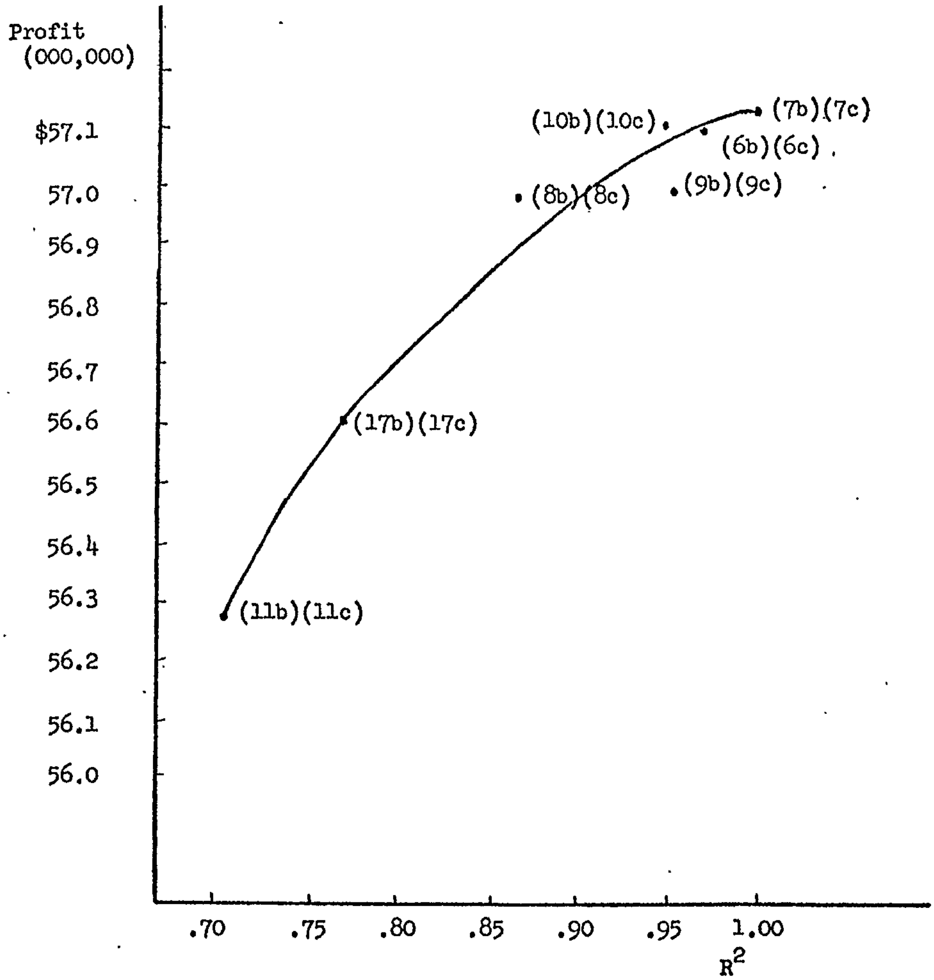


Table 1

Optimization with Estimates of Competitors' Flights

	Actual	(6b)(6c)	(7b)(7c)	(8b)(8c)	(9b)(9c)	(10b)(10c)	(11b)(11c)	(17b)(17c)	Perfect Forecasts
Total Profits ($000)	51.379	55.405	55.492	55.520	55.320	55.546	55.018	55.343	55.835
Avg. Market Share %	17.3	17.3	17.2	17.1	18.6	17.1	19.3	18.4	17.3
Avg. Load Factor %	21.8	40.5	40.4	39.7	36.8	40.6	36.2	37.2	39.8

Table 2

Comparison of Actual and Optimal Settings
of Flights Using Historical Competitors' Flights

Number of Flights

		Optimal Flights based on Estimates of Competitors' Flights Using Decision Rules								
t	Actual	(6b)(6c)	(7b)(7c)	(8b)(8c)	(9b)(9c)	(10b)(10c)	(11b)(11c)	(12b)(12c)	(17b)(17c)	Perfect Forecasts
1	4	4	4	4	3	3	4	*	3	4
2	5	6	5	5	5	5	5	*	5	5
3	6	7	7	6	6	6	6	*	6	6
4	6	3	4	5	3	3	5	*	5	4
5	6	3	3	4	2	2	4	*	4	3
6	7	5	5	4	4	5	6	*	6	5
7	8	5	4	3	4	4	6	*	6	5
8	8	4	4	4	4	4	5	*	5	4
9	6	3	3	4	3	2	4	*	5	4
10	11	7	6	5	6	6	6	*	7	6
11	10	6	6	5	7	6	7	*	7	6
12	11	4	3	3	4	3	5	*	6	4
13	9	2	1	2	3	1	4	*	5	2
14	8	8	8	7	9	8	8	*	9	8
15	8	10	9	8	10	9	9	*	9	9
16	8	4	5	5	6	5	6	*	7	4
17	8	3	4	4	6	4	6	*	6	3
18	12	8	8	8	10	9	9	*	9	6
19	12	8	10	9	12	10	10	*	10	7
20	12	2	5	5	8	5	7	*	7	4
21	10	5	4	5	7	5	7	*	7	5
22	12	10	10	10	12	10	10	*	10	8
23	14	12	13	12	15	13	13	*	13	11
24	13	5	7	7	10	8	9	*	9	8
25	12	7	5	6	9	6	8	*	8	8
26	13	13	11	11	14	12	12	*	12	12
27	14	16	15	15	17	16	15	*	15	15
28	14	9	9	9	13	10	11	*	11	10

Table 3

Simulated Profit , Average Market Share, and Average Load Factor for Airline K.

Actual Competitors Strategy

Assumed Competitors Strategy	(7b)(7c)	(8b)(8c)	(9b)(9c)	(10b)(10c)	(11b)(11c)	(17b)(17c)
(6b)	$56.990	55.012	76.150	58.765	66.871	68.814
(6c)	17.6%	17.3	21.1	17.6	21.0	21.5
	39.8%	39.5	40.3	40.1	39.8	39.9
(7b)	57.046	55.187	74.767	58.713	72.709	283.874
(7c)	17.3	17.1	19.3	17.4	19.8	64.3
	40.4	40.3	44.7	40.5	47.7	61.7
(8b)	56.879	55.344	74.647	58.578	73.592	117.795
(8c)	17.2	17.1	19.2	17.3	19.9	26.2
	39.7	39.5	44.0	39.7	46.7	61.9
(9b)	56.879	54.873	76.161	58.738	65.529	66.764
(9c)	18.1	17.8	21.0	17.9	20.9	21.5
	38.2	38.5	40.4	38.7	39.4	39.0
(10b)	57.002	55.208	76.040	58.834	67.150	83.250
(10c)	17.4	17.1	20.3	17.3	20.7	24.7
	40.1	39.4	42.0	40.6	40.2	43.1
(11b)	56.179	54.589	75.534	58.121	68.286	69.764
(11c)	19.2	19.2	21.2	19.1	20.9	21.5
	36.0	35.7	40.2	36.3	40.0	40.2
(17b)	56.503	54.944	75.683	58.332	67.194	69.392
(17c)	18.5	18.4	19.7	18.3	20.9	21.6
	37.1	36.8	42.6	37.7	39.6	39.9

Examination of the matrix yields the following conclusions:

1. If competitors set their flights based on time-dependent decision rules (7b) and (7c), (8b) and (8c), (9b) and (9c) or (10b) and (10c), which are independent of airline K's decisions, the best the firm can do is to have as good an estimate of competitors' flights as can be obtained That is, the correct assumption about rival's decision rules produces maximum profit in the first four columns of the matrix. The relationship between predictive ability and profit is shown in Figure 2, which plots the profit from column one against the correlation between assumed and actual competitors' flight levels.

2. It is important to point out that competitors' decision rules are set in the simulation, not their quarterly flight levels. For rules (11b) and (11c) and (17b) and (17c), the distinction is critical. When competitors use competitively adaptive or completely adaptive decision rules, their flight levels depend on the flights scheduled by their rivals. An aggressive market strategy on the part of any one of the airlines may lead to fierce competition and high flight levels for all airlines. A passive market strategy on the part of any of the firms can lead to lower levels of competition, higher load factors and increased industry profit.

3. If the firm is pessimistic or if management places high value on security, they might seek to guarantee the greatest profit in the most adverse circumstances and use a maximin criterion. By assuming competitors use decision rules (8b) and (8c), airline K can guarantee itself a payoff of no less than $55.344 million. Such a conservative decision criterion ignores all information in the matrix except the worst outcomes for each strategy.

4. At the opposite extreme is the optimistic maximax decision criterion. Assuming that competitors use decision rules (7b) and (7c) can lead to profit of $283.874 million for the firm. This criterion, however, allows the best payoff to blind the decision maker to potential dangers in the strategy.

5. The most frequently suggested criterion for such decision problems is a Bayesian criterion. Without sufficient information to ascribe probabilities to the likelihood of each of the competitors' strategies, each move should be considered equally likely. In the present case assuming decision rules (7b) and (7c) offers the greatest expected profits for airline K. This result is primarily due to the high payoff in the last column of the second row. Considering the unlikelihood of competitors following such a strategy shifts the Bayesian decision to (8b) and (8c) which offers expected profits of $53.169 million. This strategy for the firm becomes even more appealing when it is recognized that decision rules (8b) and (8c) dominate any other strategies for competitors.

The generation of the matrix ignored consideration of <u>optimal</u> competitive strategies which might be employed by a rational competitor. The conclusions reached above yield useful insights into appropriate strategies when the firm is able to make certain assumptions about how competitors view the market situation.

III. CONCLUSION

Empirical decision rules for competitive behavior provide the basis for simulating the consequences of a firm's marketing decisions. Results show that an "optimal" strategy for assessing competitive response in the model is to act as if the competition is following a time-dependent strategy, thus promoting a lower level of competition and higher profit for the firm. This paper shows that simulation as a decision aid has considerable promise in airline and other management settings.

FOOTNOTES

[1] This follows similar notation used in an earlier paper [5] which includes the empirical estimates of the decision rules.

[2] The effect of the timing of flight schedules has not been considered. Such an effect may be critical where optimal flights approach three daily. In addition, minimal flight constraints may be imposed by the C.A.B.

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