I. INTRODUCTION

Yield Management, also known as revenue management or perishable inventory control, is a strategy of maximizing profit from a limited capacity of product over a finite horizon by selling each product to the right customer at the right time for the right price. In other words, yield management is utilized whenever a commodity of service is priced differently depending on various restrictions on bookings or cancellation. For this reason, the concept of yield management is best applicable in the airline industry. In that particular industry, a pool of identical seats, sold for different fares are subjected to different restrictions associated with a particular fare class in order to lure customers and improve revenues.

The airline industry's problem of determining the number of seats to make available to each fare class so as to maximize total expected revenues for a scheduled future flight can be properly addressed with the application of the yield management concept by finding the right combination of passengers on the flights. The booking requests and mix of fare classes on each flight departure are controlled such that the planes are filled with the most profitable passengers.

Despite the success of numerous works in the airline yield management in the past, it was found that most of the mathematical models incorporate common simplifying assumptions and several conditions such as: the number of fare classes, arrival distribution of booking requests, treatment of system features, approximation of values, type of solution algorithm and techniques to be used, curse of dimensionality, and even the combination of any of these, that must first be identified and satisfied before these techniques could be operationally optimal or functional, which induces the computational complexities of these mathematical models.

To address the inherent complexities of current techniques employed in the study of airline yield revenue / yield management, it is necessary to develop a simulation model that will provide a flexible and realistic assessment of the actual behavior of the various booking policies employed by the airline industry.

In developing a simulation model that would be able to provide realistic behavior of the booking operation in the airline industry, the system is to be made independent of historical data, to be flexible in using different statistical distributions without altering the entire system, to be capable of immediate manipulation of all the inputs or data to make it adaptable to any given scenario, and to be less computationally demanding. Furthermore, the study is primarily based on a single leg flight with multiple fare classes that allow cancellations, no – shows and chance passengers, as customer behavior variables, with an assessment of the different booking policies such as the non – nested seat allocation, nested booking limit, and overbooking policy. Other features of the study are greatly founded by the researches of Lee and Hersh (1993), Subramanian, et. al (1999) and El – Haber and El – Taha (2004).

II. MODEL FORMULATION

The model of this particular study is formulated using licensed Arena 7.0 Rockwell software. With the use of this particular software, the system is presented in a flowchart – based model programming, which enables any user to easily appreciate and understand the logic of the entire system being modeled. Figures 1 and 2 illustrate the map of the information flow in the entire system and the map of information in the main model, respectively, that is used to describe the booking / flight reservation operation of an airline company.

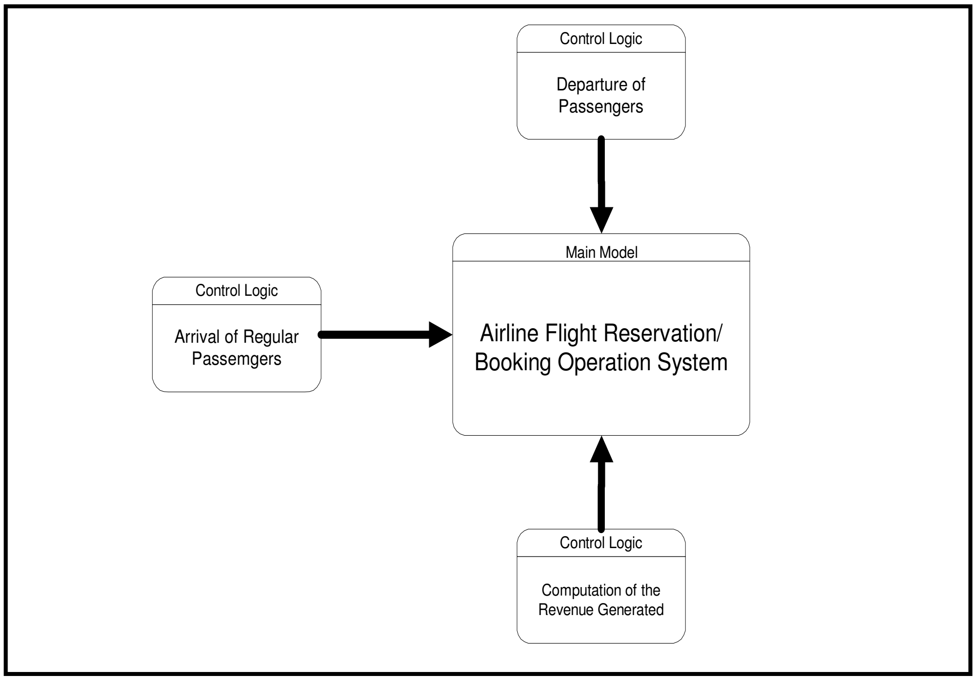

Figure 1: Map of Information Flow in the Entire System

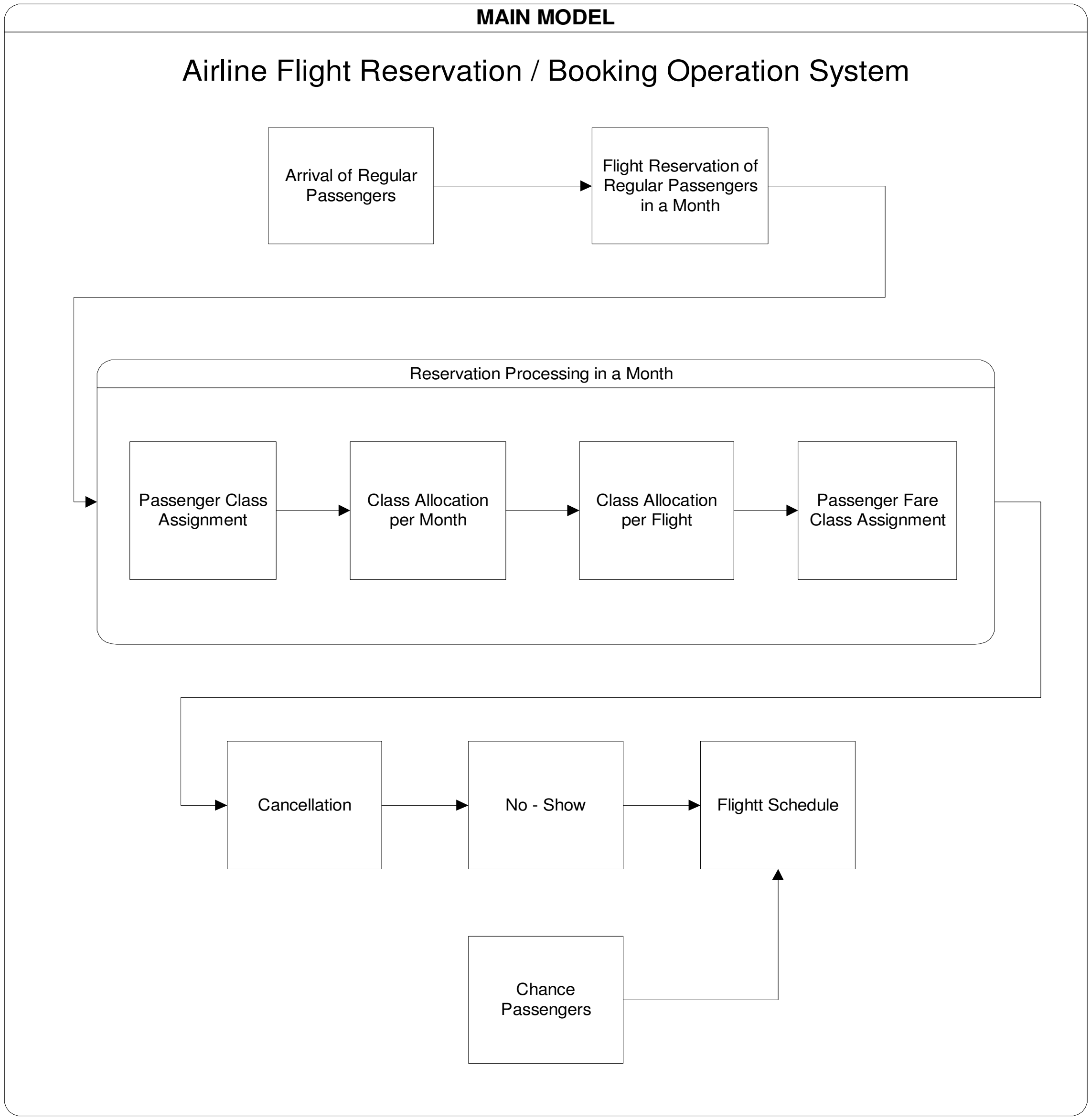

Figure 2: Map of Information Flow in the Main Model

This particular simulation model is designed to consider several decision variables that the programmer can modify from time to time depending on the need or situation to be modeled. In this particular system, there are four identified decision variables, namely: seating capacity of each flight, number of flights in a given month, number of fare classes on each passenger class and the extent of the month to which a particular passenger can reserve a flight.

In the formulated system, there can be found several sets of modules separately placed from the main model. These sets of modules can be referred to as the control logics of the main model. The individual control logic has its own series of modules for its operation.

Although these control logics run separately, it can still affect the main model by controlling the rationale behind the operation of several modules in the main model. With the use of control logics, several variables are triggered to facilitate the arrival of entities, to release specific values or to perform several functions once the control logic that manages it has also performed.

There are three (3) main control logics that can be found in the system. These control logics facilitate the operation of the arrival of regular passengers, departure of the passengers and the computation of the revenue generated as the system operates.

III. RESULTS

After the model for each booking policy for this particular study has been formulated, it will now be set to a base run in order to validate its operations. At this point in time, the models are expected to imitate the actual operation of the system identified in the airline industry.

To make it more realistic, it was assumed that the flights being modeled are the one – way route trip from Manila, Philippines (MNL) to Los Angeles, California USA (LAX), since most aircrafts used for this flight have first (1st) class cabins, and that the passengers are all adults for the purpose of assigning of ticket prices. The entire run will be for fifteen (15) years of continuous (non – terminating) operation, wherein there are twenty-four (24) hours in a day, and thirty (30) days in a month. Other inputs for the base run set – p of each model are such as the flight reservation pattern, flight capacity per month, passenger class and fare class assignment distribution, ticket price matrices per passenger class per month, and so on, were also supplied.

After all the necessary information had been encoded in each booking model for the simulation run, the data collection was the next step to undertake. All the data that was gathered were put into graphs per month for further analysis. The analysis to be done on this particular system is on a monthly basis due to the seasonality incorporated in the demand, immediately disallowing the comparison of the trends on a yearly basis. Moreover, the stabilization period of the simulation model must be identified for this non – terminating system to exclude the initialization bias in the model. Based from the graphs shown per month, which can be found in Figures 3 – 5 for each model type respectively, it can be seen that the values gathered had exhibited great fluctuation on the revenues that the system was able to generate during the 3rd to 5th year of operation. This particular observation can be particularly linked to the initialization bias of this non – terminating system. But starting on the 7th year, it can be noticed that the values had gone back to their normal pacing. This implies that all relevant data to be gathered for the succeeding runs and analysis for the sensitivity analysis would start only at the 7th year.

Based from the graph in Figure 3, since the non – nested seat allocation model implements a fixed capacity / allocation for the observed increase in the revenue in this model can be attributed to the fact that this particular policy prioritizes the higher – fare passengers over the lower – fare ones.

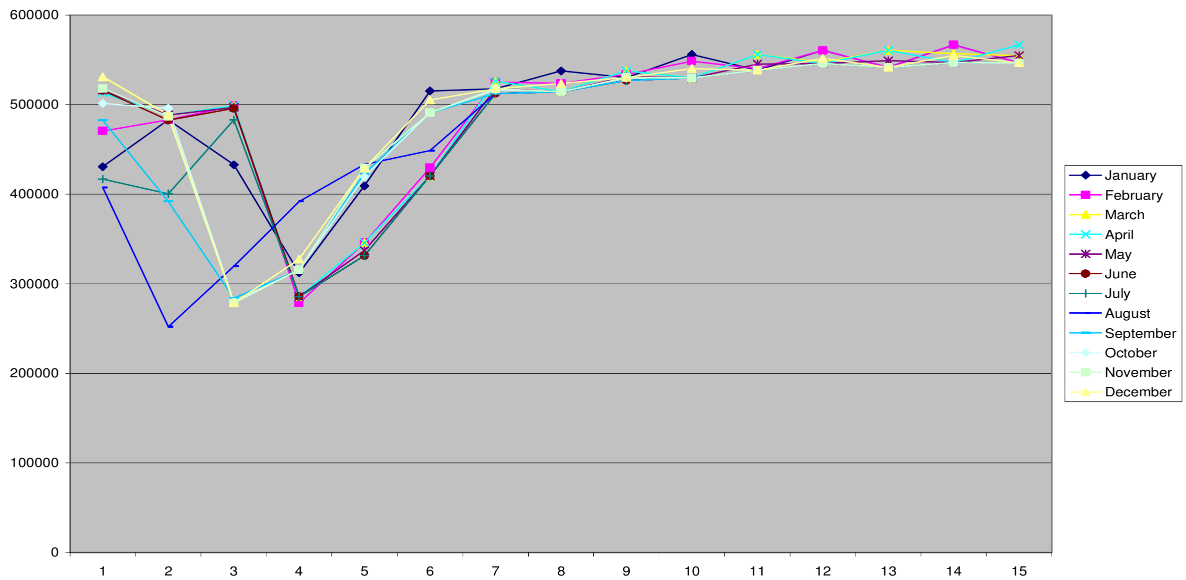

Figure 3: Base Run Results of the Non – nested Seat Allocation Model

For each passenger class, the revenues generated were expected to be based solely on the number of passengers in the system, depending on their indicated passenger class and fare classes.

The performance of the nested booking limit model produced much better results in terms of revenues.

With this policy, it is practiced that higher – fare passengers, who already have allocated number of seats, can still eat up the allocated seats of the lower – fare passengers whenever there are available seats. In such case, more revenues are generated for the system. This observation is found in Figure 4.

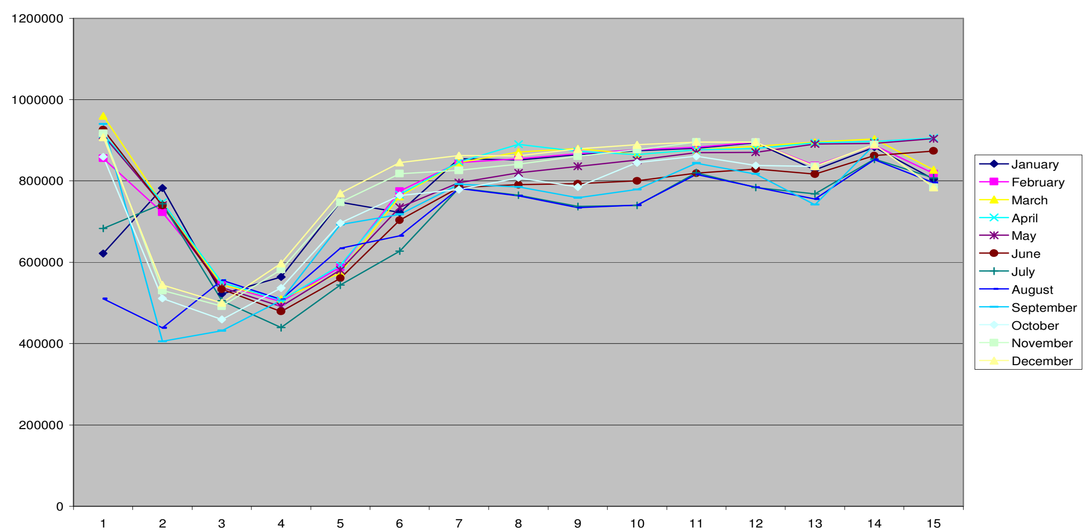

Figure 4: Base Run Results of the Nested Booking Limit Model

Lastly, as seen in the graph presented in Figure 5, the overbooking policy model also yielded improved revenues for the system. Since this particular policy allows the entrance of waitlisted passengers in the system as they replace those regular passengers who had cancelled their flight reservations at any given point in time in the booking period, additional revenues can be generated by the system.

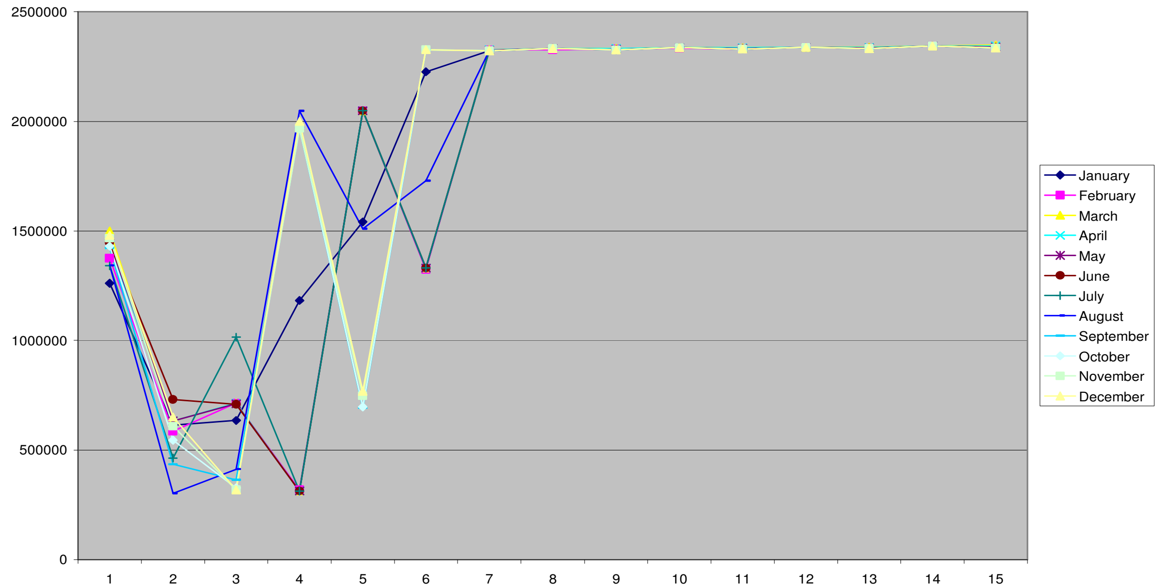

Figure 5: Base Run Results of the Overbooking Policy Model

IV. SENSITIVITY ANALYSIS

The non-nested seat allocation model, nested booking limit approach model and the overbooking model are the types of model used at this particular phase, with the purpose of identifying the responses or reactions of each type of model with each customer behavior variables in a particular airline operation. The sensitivity runs were conducted as three types of models were made to separately run, the same model structure was used, and the rest of the customer behavior variables were held constant as one particular variable is varied. The result of the base run set – up of each type of model had been plotted against the results of the system's response as the values of each type of customer behavior variables were varied one at a time for further analysis.

V. DESIGN OF EXPERIMENT

As the sensitivity analysis was accomplished, the airline yield management simulation model created was set for another batch of runs for the values to be encoded in the Design of Experiment phase. This particular experiment was conducted to further validate the performance of the airline yield management simulation model found in the sensitivity analysis chapter and to assess and ascertain how variations in customer behavior variables affect the revenue across the different booking policies.

At this particular phase, the Design Expert 6.0 Software was used and the type of design for this experiment was chosen to be the General Factorial Design, because there is only one categorical factor, which are the 3 different booking policy models with the base run set – up values, to be included in the experiment; while the rest of the factors, which are the customer behavior variables, are only two factorial. The design summary can be found in Table 1.

Table 1. Design Summary

Design Summary							
Study Type	**Factorial**		Experiments	**48**			
Initial Design	**Full Factorial**		Blocks	**No Blocks**			
Center Points	**0**						
Design Model	**2FI**						
Response	**Name**	Units	Obs	Minimum	Maximum	Trans	Model
Y1	**peak season**		**48**	**3.42846**	**10.4627**	**None**	**2FI**
Y2	**lean season**		**48**	**3.38628**	**10.3442**	**None**	**2FI**
Factor	Name	Units	Type	Low Actual	High Actual		
A	**reg psngr arrival**		Categorical	**inc 50%**	**dec 50%**	Levels:	**2**
B	**cancellation**		Categorical	**0%**	**75%**	Levels:	**2**
C	**no show**		Categorical	**0%**	**75%**	Levels:	**2**
D	**chance psngr arrival**		Categorical	**inc 50%**	**dec 50%**	Levels:	**2**
E	**model type**		Categorical	**non-nested, nested, overbooking**		Levels:	**3**

As soon as the factors and its levels had been encoded in the model, the software automatically generated the combinations of each factor setting to be varied in the simulation model to start the runs. Also, since the airline industry is identified to have seasonality, the months for the peak season and lean season are segregated for the responses in the design; thus, the experiment would need two responses or values to be encoded for the two types of season for each configuration runs. Furthermore, there were some changes made on the values of the inter-arrival time of the regular passengers to have better results than the values used in the base run set – up and sensitivity analysis.

Based on the results of ANOVA generated by the software, the created model is significant with a value less than 0.01% for both peak and lean seasons.

It can also be observed from the results shown in Appendix A that almost all the factors are significant except for factor B (Cancellation) for both types of season.

However, only the interaction of factors AE (interaction of the regular passengers' arrival and model type) and BE (interaction of cancellation and model type) has a value of probability > F less than 5%, which means that only these two interactions are significant, for both seasons, and with the addition of the interaction BD (interaction of cancellation and chance passengers' arrival) to be significant for the peak season only.

Logically, interaction BD is important because during the peak season, it is critical to note the cancellation behavior of the passengers from an observed increased number of regular passengers arriving at this particular season and the arrival behavior of the chance passengers in order to compensate for those regular passengers who had cancelled, for which it could greatly affect the revenue to be generated by the season using any particular model type.

Moreover, based from the results of the ANOVA, it can be concluded that it was very important to identify the different booking policies to be used in the system because it can truly make distinguishing effects in the revenue that the system can generate, as well as play significant interactions with several customer behavior variables that can further improve the results of the system.

Using the one factor plot that the software has generated for both season, the analysis made on the sensitivity and effects of the customer behavior variables in the system can further be validated.

Also, in order to determine the impact of the interaction of customer behavior variables and the different booking polices to the revenue generated by the system, the interaction graphs of the model types with each customer behavior variable that were generated from the design of experiments were analyzed.

VI. CONCLUSIONS

Based on the results of the base set – up runs of each model that incorporate each booking policy, identified as the non – nested seat allocation, nested booking limit and overbooking policy, it can be ascertained that each booking policies have its own distinguishing effects in the revenue generated by the system. Since the non – nested seat allocation model implements a fixed capacity / allocation for each passenger class, the revenues that were generated were expected to be based only on the number of passengers in the system, depending on their indicated passenger class and fare classes. The performance of the nested booking limit model has produced much better results in terms of revenues. The observed increase in the revenue in this model can be attributed to the fact that this particular policy prioritizes the higher – fare passengers over the lower – fare ones. With this policy, it is practiced that higher – fare passengers already has their allocated number of seats and can still eat up the allocated seats of the lower – fare passengers whenever there are available, which primarily added more revenues for the system. Lastly, the overbooking policy model also yielded more improved revenues for the system. Since this particular policy allows the entrance of waitlisted passengers in the system as they replace those regular passengers who had cancelled their flight reservations at any given point in time in the booking period, additional revenues can be generated by the system.

According to the results and analyses that were generated from the sensitivity runs and design of experiment, it can be concluded that each customer behavior variables has its unique way of greatly affecting the results of the revenues in the airline yield management study.

The inter-arrival time of the regular passengers determines the demand that the system has at a particular point in this, which makes it the main determinant of the revenue that the system can generate throughout its operation because the number of passengers entering the system is greatly dependent on the values that will be inputted for this particular variable where the revenue factor (ticket prices for each type of fare class) will be multiplied.

Cancellation probability rates were also a significant factor in determining the revenues that the system that was modeled can generate. Having to include cancellation probability rates in the system would mean that, at any point in time after the booking / reservation process, several passengers could withdraw their reservations. Upon withdrawing a reservation, the system has lost the full realization of the revenue gained from those passengers since each passenger that cancels their reservations would mean a refund, depending on the passenger class and fare class of that certain passenger.

Another customer behavior variable is the no – show probability rate. The no – show probability rates in the system also plays an important role in the revenue in the airline yield management study. Similar thought with cancellation, no – show probability rates determine the odds that passengers would forego their flight reservations exactly on the day of their flight schedule itself. As supported by the sensitivity analysis and design of experiment results across the three types of models, as the no – show probability rates increases, the revenue generated by the system decreases due to the fact that numerous passengers are not showing up during their flight schedules, thus, getting refunds from the system, which can be supposedly the actual revenue generated. Also, because of the nature of this variable that lost revenues can only be known on the actual flight schedule, the system can't immediately replace those passengers who didn't show up with overbooked passengers or with nesting the booking requests from the start to compensate for the loss in revenue at the flight schedule.

The last customer behavior variable included in this particular study is the arrival of the chance passengers in the system. Although the entrants of this type of passengers in the system are only during the flight schedule itself, it can still be observed that this particular variable can still greatly affect the performance of the revenue that the system can generate.

REFERENCES

Brumelle, S. and McGill, J. *Airline Seat Allocation with Multiple Nested Fare Classes*, Operation Research, 1993; 41 (1): 127 – 137

Chen, V. Günther, D. and Johnson, E. *A Markov Decision Problem Based Approach to the Airline YM Problem*, 1998: 1 - 24

Coté, J., Marcotte, P., and Savard, G. *A Bilevel Modeling Approach to Pricing and Fare Optimization in the Airline Industry*, Journal of Revenue and Pricing Management, 2003; 2(1): 23 – 36

Curry, R. *Optimal Seat Allocation with Fare Classes Nested by Origins and Destinations*, Transportation Science, 1990; 24 (3): 193 – 204

El-Haber, S. and El-Taha, M. *Dynamic Two-Leg Airline Seat Inventory Control with Overbooking, Cancellations and No-shows*, Journal of Revenue and Pricing Management, 2004; 3 (2): 143 – 170

Lautenbacher, C. and Stidham, S. (1999), *The Underlying Markov Decision Process in the Single-Leg Airline Yield Management Problem*, Transportation Science, 1999; 33 (2): 136 – 146

Lee, T. and Hersh, M. (1993), *A Model for Dynamic Airline Seat Inventory Control with Multiple Seat Booking*, Transportation Science, 1993; 27 (3): 252 – 137

Pak, K. and Piersma, N. *Airline Revenue Management: An Overview of OR Techniques 1982 – 2001*, Erasmus Research Institute of Management (ERIM) Report Series in Management, 2002: 1 - 23

Pak, K., Dekker, R., and Kindervater, G. *Airline Revenue Management with Shifting Capacity*, Erasmus Research Institute of Management (ERIM) Report Series in Management, 2003: 1 – 25

Ringbom, S. and Shy, O. *The "Adjustable – Curtain" Strategy: Overbooking of Multi-class Service*, Journal of Economics, 2001: 73 – 90

Rothstein, M. *An Airline Overbooking Model*, Transportation Science, 2001; 5 (2): 180 – 192

Subramanian, J., Stidham, S., and Lautenbacher, C. *Airline Yield Management with Overbooking, Cancellations, and No-shows*, Transportation Science, 1999; 33 (2): 147 – 167

Talluri, K. and van Ryzin, G. *Revenue Management Under a General Discrete Choice Model of Consumer Behavior*, Management Science, 2001;50 (1):1– 36

Turkmen, B., Bulgak, A. and Akgunduz, A. *A Revenue Opportunity Model for Airline Industries for the Deregulated Global Market*, 2004: 1 – 3

Appendix A: ANOVA Results for the Peak Season

Response:	**peak season**					
ANOVA for Selected Factorial Model						
Analysis of variance table [Partial sum of squares]						
Source	**Sum of Squares**	**DF**	**Mean Square**	**F Value**	**Prob > F**	
Model	118.5741344	20	5.928706722	10.65898785	< 0.0001	**significant**
A	15.29839043	1	15.29839043	27.50437242	< 0.0001	
B	0.149614351	1	0.149614351	0.268985737	0.6082	
C	3.563782269	1	3.563782269	6.407183501	0.0175	
D	9.023051285	1	9.023051285	16.22218782	0.0004	
E	36.31472708	2	18.15736354	32.64440735	< 0.0001	
AB	0.093749086	1	0.093749086	0.168547782	0.6846	
AC	0.122730357	1	0.122730357	0.220652065	0.6423	
AD	0.516967616	1	0.516967616	0.929435676	0.3436	
AE	15.45093223	2	7.725466114	13.88931065	< 0.0001	
BC	0.090248637	1	0.090248637	0.162254463	0.6903	
BD	2.904861481	1	2.904861481	5.22253582	0.0304	
BE	32.05726572	2	16.02863286	28.81724647	< 0.0001	
CD	0.136566402	1	0.136566402	0.245527345	0.6243	
CE	0.816910663	2	0.408455331	0.734345721	0.4892	
DE	2.034336845	2	1.017168422	1.828726965	0.1800	
Residual	15.01785008	27	0.55621667			
Cor Total	133.5919845	47				

Note:

A Regular passengers' arrival
B Cancellation
C No - show
D Chance passengers' arrival
E Model type
AB Interaction of regular passengers' arrival and cancellation
AC Interaction of regular passengers' arrival and no – show
AD Interaction of regular passengers' arrival and chance passengers' arrival
AE Interaction of regular passengers' arrival and model type
BC Interaction of cancellation and no – show
BD Interaction of cancellation and chance passengers' arrival
BE Interaction of cancellation and model type
CD Interaction of no – show and chance passengers' arrival
CE Interaction of no – show and model type
DE Interaction of chance passengers' arrival and model type

Appendix B: ANOVA Results for the Lean Season

Response:	**lean season**					
ANOVA for Selected Factorial Model						
Analysis of variance table [Partial sum of squares]						
Source	**Sum of Squares**	**DF**	**Mean Square**	**F Value**	**Prob > F**	
Model	113.60655	20	5.680327498	9.978440622	< 0.0001	**significant**
A	11.98874264	1	11.98874264	21.06022172	< 0.0001	
B	1.15289622	1	1.15289622	2.025254086	0.1662	
C	3.221141682	1	3.221141682	5.658471456	0.0247	
D	7.55810356	1	7.55810356	13.27706679	0.0011	
E	35.54864404	2	17.77432202	31.22355479	< 0.0001	
AB	0.289174863	1	0.289174863	0.507983773	0.4821	
AC	0.06148722	1	0.06148722	0.108012535	0.7450	
AD	0.68689632	1	0.68689632	1.206647706	0.2817	
AE	11.90051913	2	5.950259563	10.45262122	0.0004	
BC	0.149602068	1	0.149602068	0.262800931	0.6124	
BD	2.030045184	1	2.030045184	3.566112224	0.0698	
BE	35.79663152	2	17.89831576	31.44137043	< 0.0001	
CD	0.081698102	1	0.081698102	0.143516312	0.7078	
CE	0.619918613	2	0.309959307	0.544495108	0.5864	
DE	2.521048805	2	1.260524402	2.2143209	0.1287	
Residual	15.37002105	27	0.569260039			
Cor Total	128.976571	47				

Note:
A Regular passengers' arrival
B Cancellation
C No - show
D Chance passengers' arrival
E Model type
AB Interaction of regular passengers' arrival and cancellation
AC Interaction of regular passengers' arrival and no – show
AD Interaction of regular passengers' arrival and chance passengers' arrival
AE Interaction of regular passengers' arrival and model type
BC Interaction of cancellation and no – show
BD Interaction of cancellation and chance passengers' arrival
BE Interaction of cancellation and model type
CD Interaction of no – show and chance passengers' arrival
CE Interaction of no – show and model type
DE Interaction of chance passengers' arrival and model type