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Anthony Narsing

Macon State College, anthony.narsing@maconstate.edu

Terry Sanders

Macon State College, terry.sanders@maconstate.edu

Len Kistner

Fort Valley State University, kistnerl@fvsu.edu

Jerry Williams

Macon State College, jerry.williams@maconstate.edu

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MANAGING RENTAL CAR BUSINESSES IN THE NEW ECONOMY: USING A MULTIVARIATE DECISION MODEL APPROACH

**Anthony Narsing
Macon State College**

**Terry Sanders
Macon State College**

**Len Kistner
Fort Valley State University**

**Jerry Williams
Macon State College**

ABSTRACT

U.S. rental car organizations are having to modify their business models to adapt to the new economy, which includes increased fuel costs, reduced business and leisure travel, and reduced resale of low mileage rental units. Revenue is negatively impacted due to increased maintenance as a result of higher mileage requirements placed on the rental inventory. Changes in the depreciation allowance on the rental car fleet reduced the potential value of vehicles by requiring fleet operations managers to maintain the fleets for longer periods of time. This article presents a multivariate decision-making model, which used in conjunction with in-house performance indicators, will assist operations managers in understanding specific variables likely to impact rental car revenues and optimize their decisions regarding available assets.

INTRODUCTION

The rental car industry flourished for many years through relationships forged with the so-called big three automotive manufacturers. Deep discounts enjoyed by rental car companies allowed them to replenish fleets and sell low-mileage vehicles for high profits in the consumer marketplace. Unfortunately this scenario has changed with the new economy. Increasing costs of fuel, replacement parts and tires; are adversely affecting many segments of the automotive market, but especially rental car companies purchasing and maintaining rental car fleets.

Several key factors are impacting revenue in this industry segment. During the period of fall 2008 through fall of 2012 the price of gasoline increased from an average of \$2.50 per gallon to an average of \$3.73 in today's market. Some

states experienced increases as high as \$5.99 per gallon during this time period (Gas Buddy.com, 2012). This trend is reflected in decreases in business and leisure travel, reductions in the numbers and prices of rental units and increased maintenance costs.

The airline and hotel industries along with leisure travel are declining, which puts additional pressure on car rental companies to further modify or change their existing revenue models. Airlines increased their profit margins from 5.3% to 6% during the 12 months from the 2nd quarter 2011 to the 2nd quarter of 2012. However, this increase includes \$991 million in baggage fees and \$661 million in reservation change fees and the total of \$1.6 billion represents 70% of the profit for quarter 2 of 2012. Total passenger loads for the first 6 months of 2012 indicate virtually no increase over 2011, an early indication that flat passenger

loads won't provide expected revenues for the rental car market from airline passengers (BTS.Gov, 2012).

Fuel costs have negatively impacted both business and leisure travel from 2007-2011. The hotel occupancy rate for 2009 was the worst on record during those five years with an average occupancy rate of 66%. The average hotel occupancy rate has increased since 2009 to nearly pre-recession levels. For example, occupancy rates rebounded to 74% for 2011 and are keeping pace so far in 2012. Unfortunately, hotel occupancy projections are lower again for the remainder of 2012 and 2013 due to the volatile fuel market (Smith Travel Research, 2012).

According to *Auto Rental News.com*, the overall inventory for rental car companies decreased from a high of 1.861 million units in 2007 to a low of 1.629 million units in 2010. The total car rental fleet increased to 1.76 million units during 2011, an increase of 8%. Revenue increased from \$20.5 billion in 2010 to \$22.4 billion during 2011. The revenue figures had not been released for 2012 when this article was completed and will reflect the Federal government's attempt to ease losses with the bonus depreciation program when they are released. This program allows rental car companies to write off the entire cost of a new rental unit in year one resulting with little or no tax liability. Once this ends, the depreciation decreases to 50% in 2012 and 0% in 2013.

The decrease in numbers of rentals per year forced rental car companies to hold on to inventory longer than usual during 2010 which resulted in an increase in maintenance costs. For example, the overall repair cost per mile per unit increased from \$0.014 in 2009 to \$0.015 in 2010 and dipped slightly in 2011 to \$0.013. The reduction in repair cost per mile is a result of replacing older vehicles with newer cars in order to take advantage of the accelerated 100% depreciation for the year of 2011. Average

maintenance costs per month increased in 2009 and 2010, at \$32 per unit and increased to \$34 per unit in 2011. These changes were due primarily to the increase in oil prices and the requirement that newer vehicles use expensive synthetic oil for scheduled oil changes. Maintenance on tires increased from \$101 per tire during 2009 to \$103 during 2010 and \$108 during 2011. This is an increase of 7% during the past three years due primarily to higher petroleum costs (Antich, 2012).

The discussion above suggests that rental car company managers face ongoing changes in a variety of key variables. Properly responding to these changes in the environment is critical to rental car company profitability. This article presents a multivariate decision-making model, which used in conjunction with in-house performance indicators, will greatly assist operations managers in understanding specific variables likely to impact rental car revenues, and allow them to optimize their decisions regarding available assets.

LITERATURE REVIEW

The research literature identifies a number of deterministic models, which are designed to address revenue management in varying industries. More specifically, the authors focused on those which centered their attention on the rental car industry. Some of the issues which these models attempt to address are highlighted below followed by a brief commentary about their shortcomings.

Twenty years ago United States automobile manufacturers purchased the majority of major car rental companies and flooded them with their vehicles. As the economy improved, changes in the price structure forced the rental car business to follow the airline paradigm of applying revenue management. Revenue management, the practice of using booking policies, together with data information systems, aims to increase revenues by intelligently matching capacity with demand (Belobaba, 1987; Weatherford and Bodily, 1992; Gallego and Van Ryzin, 1997).

Unfortunately, this approach presented difficulties within the car rental industry. It failed to address specific issues surrounding asset management for businesses operating in a downturn economy. Rental car companies found themselves holding on to their assets (i.e. rental units) longer than usual. As a result, this practice gave rise to increased maintenance and liability issues, which many of the deterministic models failed to address or explain when discussing revenue management. Most of these models are static in nature, and thus cannot fully account for dynamic changes.

Researchers agree that all rental car companies face an uphill battle in their dynamic pricing practices, because there are an increasing number of variables to take into account. Altman and Helms (1995) noted that competitive pricing is one of the most critical attributes that a rental car company must possess in order to attract customers. In addition to pricing, there are other factors to consider, such as different car classes, arrival dates, rates which can change daily, and time of rental. Most deterministic models simply identify these variables, but fail to fully explain their interaction, or significance in explaining variation in revenue.

A common theme in the revenue management literature is to focus on profit maximization by matching capacity with demand. One particular method in dealing with this complexity involves risk pooling, where rental locations can be grouped in pools to gain access to each other's vehicles. In the rental car industry, revenue management models can be designed to allocate resources to the products, allocate resources to the customer, set prices, and allocate resources to the market.

Predictive models typically developed for this industry include unit pricing, allocating resources to markets and dynamic reallocation. The unit pricing model is used consistently in the rental car industry; it includes data such as location, car type, anticipated demand, duration of rental, and competitor pricing. Once bookings

begin, demand forecasts are updated. Then demand is considered relative to available resources, given customer preference of car type. The model which allocates resources to markets considers production capacity, which can be optimized across and within markets. A variation of the preceding model involves dynamic reallocation, which targets short-term adjustments in the allocation of resources across markets.

RESEARCH SETTING AND ISSUE

A typical rental car company aggregates and compiles its operational and financial data monthly. Internal reports are generated from these databases and disseminated to both district and branch managers who review indicators such as utilization, and any identifiable trending associated with travel. Short-term revenue implications are assessed based on current market conditions, and adjustments are often initiated to align with long-term corporate strategic goals.

A nation-wide rental car company provided a subset of its operational and financial databases for one of its small markets covering a three-year period from 2009 to 2011 to assist with this research project on the condition that their identity remained anonymous given the sensitivity and priority nature of the information. There are four rental locations within 50 miles of one another included in this database. Two of its largest centers are within 25 miles of each other, which allows for access to its fleet to meet specific customer demand. One of these two locations is situated near a military base, while the other is strategically positioned in an industrial dominated sector. The other two locations service smaller geographical regions with a focus on serving rural customer needs. During this three-year period and well into 2012, the rental car agency recognized that its revenues were plummeting, as demand fluctuated affecting both fleet capacity and utilization. It recognized the need to institute changes to its current business plan given the volatility within

the market-place. According to the operations manager, the decline in profits was linked to increases in fuel prices, inadequate depreciation, reduced discounts on new acquisitions from automobile manufacturers, and a softened used car market place. In 2012 the used car re-sale market improved because manufacturers reduced their fleet allocations and eliminated “deep” discounts.

In the past, rental car agencies depended less on rental revenue for profitability. Significant profits were realized from the re-sale of rental units, which were leveraged against the “deeply” discounted purchase price. In fact, rental revenues were used to service each unit’s operational costs until it was time to dispose of the inventory. While there is no industry standard, it was common practice in the rental car agency in this study to dispose of a rental unit when it reached about 21,000 miles, according to the operations manager. Unfortunately, with all of the changes discussed above, this practice was quickly abandoned as they were now faced with keeping their units much longer in their fleets.

Given the need for change, the rental car operations manager was keenly interested in the deterministic multivariate model proposed in this research. More specifically, he is interested in determining how the information derived from the model can be effectively implemented within their decision-making process. This allows the rental agency to achieve its long-term strategic goals and to maximize fleet revenue. A methodology for the multivariate decision model is proposed in the next section.

METHODOLOGY

The following sections address variable definition, model formulation, and model building approaches.

Defining Variables

This section defines both the predictor and indicator variables for the multivariate decision model. The rental car company’s database captures vital information about the company’s operations for all four of its market locations. Some of the predictor variables extracted from the rental car database are shown in Table 1. These fields include: revenue (REV), number of rentals (NUMREN), number of rental days (RENDAYS), fleet size (FLT SIZE), revenue per day (REV PDAY), revenue per rental unit (REV UNIT), average number of rentals per month (AVEREN) and utilization (UTIL).

Based on interviews with the operations manager, it was determined that interest in additional predictor variables needed further investigation to determine potential impact on revenues. An expanded database was created to provide these predictor variables: nationwide monthly gasoline prices (GASOL), consumer price index (CPI), regional population data (POP DAT), and regional monthly unemployment data (UNEMP).

Three dummy variables were added to reflect potential effects due to location, seasonality or quarterly periods. These variables include: Location (REGION1, REGION2, REGION3, and REGION4), Season (FAL, WIN, SPR, SUM), and fiscal year Quarter (QUAR1, QUAR2, QUAR3, and QUAR4).

The objective of the database analysis was to identify a representative subset from the variables shown in Table 1 for the purpose of fitting the multivariate deterministic model. The model’s predictive capability along with the rental car agency’s in-house performance indicators would be used to enhance to decision making to maximize rental car fleet revenues.

Several endogenous variables are identified to help explain variation in revenue. Some variables were intuitively identified based on their ability to globally impact the economy such

TABLE 1
DEFINITION OF PREDICTOR VARIABLES

<i>Definition of Variable</i>	<i>Short Variable Name</i>
Y = Monthly Rental Car Revenue (thousands of dollars)	<u>REV</u>
X_1 = Seasonal Segmentation (fall, winter, spring and summer) ~ Dummy Variable	<u>FAL</u> , <u>WIN</u> , <u>SPR</u> , <u>SUM</u>
X_2 = Quarterly Segmentation (<u>Q</u> ₁ , <u>Q</u> ₂ , <u>Q</u> ₃ , and <u>Q</u> ₄) ~ Dummy Variable	<u>QUAR1</u> , <u>QUAR2</u> , <u>QUAR3</u> , <u>QUAR4</u>
X_3 = Regional Location (four locations within a 50 mile radius) ~ Dummy Variable	<u>Region1</u> , <u>Region2</u> , <u>Region3</u> , <u>Region4</u>
X_4 = Regional Population Data (thousands of people)	<u>PopDat</u>
X_5 = Regional Monthly Unemployment Data (%)	<u>UnEmp</u>
X_6 = Nationwide Monthly Price for Regular Gasoline (\$ per gallon)	<u>Gasol</u>
X_7 = Number of Rentals per month (expressed in hundreds)	<u>NumRen</u>
X_8 = Total Number of Days Cars were Rented Monthly	<u>RenDay</u>
X_9 = Average Number of Rentals per Month (days)	<u>AveRen</u>
X_{10} = Revenue per Unit (\$ per unit)	<u>RevDay</u>
X_{11} = Fleet Size (number of units) per month at each location	<u>FltSize</u>
X_{12} = Fleet Utilization (%)	<u>Util</u>
X_{13} = Average Number of Days per Rental Unit ('000)	<u>RevUnit</u>
X_{14} = Advertising Expense ('000)	<u>AdvExp</u>
X_{15} = Consumer Price Index (CPI) ('00)	

as gasoline price, consumer price index, and unemployment rate, which influences spending. As fuel prices increase, both consumers and businesses tend to alter their consumption levels.

Exogenous variables help to capture this effect, but these are difficult to accurately quantify. For instance, businesses often ask their employees to use public transportation or taxis, rather than incur the cost of a rental car. Rental car companies have no way to counteract such practices, except to offer further rate reduction, which undermines revenue in the short term. As the general price levels for goods and services rise, both consumers and businesses adjust consumption levels to meet existing and future demand. Families are likely to defer travel, while businesses enact policies whereby employees are compensated for the use of their own vehicles. Rental car companies can do little to alter consumer and business practices. Instead, they

are motivated to seek cost reduction through efficient allocation and maintenance of an optimal mix of units and size (Cook and Weisberg, 1985).

Model Formulation

The basic structure for building the multivariate decision model is derived from using the general linear regression methodology, which utilizes multiple explanatory variables. This model is commonly referred to as a multivariate regression model in the statistical literature (Rousseeuw, 1984). Equation 1 provides the generalized form, whereas equation (2) presents the formal structure. The dependent variable, Y defines *Revenue*, while the variables denoted by X_i represent the list of predictor and indicator variables (i.e. dummy variables). As shown in equation (1) the two components include a deterministic and a random error.

$$Y\text{-values} / X\text{-values} = \text{deterministic} + \text{random error} \dots \dots \dots (1)$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k + \varepsilon \dots \dots \dots (2)$$

The deterministic component represents the explained variation about the response variable, whereas the random error accounts for the unexplained variation. Unexplained variation is the result of occurrences which often the user does not have control over, such as a customer's decision to use public transportation or carpooling in lieu of renting a car.

The multivariate regression equation shown in (3) must be expressed in its algebraic form before data processing can be facilitated.

$$E(Y / (X_1i, X_2i, \dots, X_ni)) = b_0 + b_1 X_1i + b_2 X_2i + b_3 X_3i + \dots + b_n X_ni \dots \dots \dots (3)$$

Equation (3) is re-written in (4) to include the random error component, ε_i which helps to capture unexplained variation as described above.

$$E(Y / (X_1i, X_2i, \dots, X_ni)) = b_0 + b_1 X_1i + b_2 X_2i + b_3 X_3i + \dots + b_n X_ni + \varepsilon_i \dots \dots \dots (4)$$

Eliminating the i indices from (4) produces the form in (5), which will be used to display the output from Minitab.

$$Y / (X_1, X_2, \dots, X_n) = E(Y / (X_1, X_2, \dots, X_n)) + \varepsilon = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + \dots + b_n X_n + \varepsilon \dots (5)$$

In summary, the basis for developing the multivariate decision model in the next section will be based on fitting the model using the statistical structure defined above in (5). The Minitab outputs will be discussed in the results section of this article.

FIGURE 1
MODEL BUILDING ALGORITHM

Model Building

The model building algorithm is illustrated in the flowchart in Figure 1. There are four stages.

Stage 1 involves conducting a preliminary investigation of the predictor variables. Stage 2 requires assessing the model's goodness-of-fit using the complete set of variables, while stage 3 uses several predictor variable reduction techniques to identify a suitable subset. Stage 4 completes the model building algorithm using transformation methods to fit a model to the data.

If a model can't be identified after stage 4, then the process of fitting the model to the data ends. The researcher must decide if added investigation is warranted by re-examining its experimental design for possible improvements or design changes.

In stage 1, a preliminary analysis using a correlation matrix and scatter plots is carried out. This is a necessary first step in identifying any spurious correlation effects, or relationships which exhibit unusually high degrees of correlation, which can ultimately give rise to the existence of multicollinearity in the model. Such conditions can adversely affect the integrity of the model's behavior and performance.

Scatter plots are particularly useful for revealing specific relations, which can assume either a linear or non-linear form. Linear forms when identified can be adapted into the model without much difficulty. Non-linear relations present challenges, but non-linear forms such as exponential or even polynomial relationships (i.e. quadratics) can be easily detected using simple scatter plots. The key to using these two basic statistical tools at the beginning of the model building process is minimizing any noise through early detection associated with specific predictor variable behavior. In summary, the completion of stage 1 allows for identifying probable relations among predictor variables;

however, there is no insight about which variables will be included in the model.

Stage 2 represents the first attempt to fit the model by using the complete set of predictor and indicator variables. If a reasonably good fit is achieved, the model building process stops and moves towards discussion of results. If a fit is undesirable, the process continues to stage 3 in the algorithm. The decision to stop or proceed further to the next stage in the model building process is based on assessing the model's goodness-of-fit. In this research, two parameters are available for assessing goodness-of-fit in regression analysis. The use of R-square and Se, the standard error of the regression, are both appropriate and acceptable statistical parameters. However, it is generally accepted by researchers to report R-square, because it has a defined range (i.e. 0 d" R-square d" 1) and is also intuitive to convey. Sometimes, there is a preference and tendency to report the adjusted R-square, if the researcher suspects an over-fitting associated with the model. Over-fitting simply implies that the model includes an unusual number of variables, which have no explanatory power.

If a fit cannot be identified from stage 2, then the process shifts to stage 3. During this stage, predictor variable reduction technique methodologies (i.e. includes stepwise, forward selection, backward elimination and Variance Inflation Factor) are used to identify a fit. Predictor variable reduction techniques are quite powerful when faced with a large set of variables (i.e. >100). The data set used in this research is limited to 22 predictor variables, almost half of which are dummy variables. In other words, caution must be exercised with this methodology because it could lead to an oversimplification of the model. Essentially, the model could result in a less than desirable fit, and with very little explanatory power.

A researcher doesn't have the luxury of using a larger set of predictor variables because the rental car operator's focus is on profits, and not

on collecting data to build statistical models. Another alternative to using these three variable reduction techniques is to use the variance inflation factor (VIF) methodology, which is particularly useful when given a smaller set of predictor variables. Stage three results can be used to compare to those found in stage 2. That is, comparing the full model in stage 2 with the reduced model in stage 3.

When variable reduction techniques don't allow for an adequate fit to the model, researchers are afforded with transformation techniques such as logarithmic, polynomial, inverse ones in hopes of providing an improved fit. It is best for transformation to be identified prior to fitting the model. This information can sometimes be detected when discussing the data set with the end user, where intuitive insights can help identify potential relationships.

For example, the operations manager indicated that increases in fuel prices resulted in declined rental units. In this case, it would be useful to use an inverse relation when fitting the "GASOL" variable. A researcher's objective is to fit the data to the best predictive model. Use of transformation techniques can serve to overfit and complicate the multivariate regression model. However, use of logarithmic or quadratic transformations can be difficult to interpret for the end user, the rental car operator. In general, while transformations can lead to an improved fit with the model, a major setback lies in its interpretation within the model.

If a satisfactory model can't be found using the model building algorithm, the only recourse is to stop and revisit the nature of the data.

Researchers are often confronted with this problem and must weigh the cost versus the benefits of devoting added resources to derive a predictive multivariate model. The rental car operator must decide if it is willing to invest resources into building a database where the information collected will lead to effective predictive modeling, and, more importantly to disseminate this information in its decision-making process.

RESULTS

Stage 1 of the model building algorithm (i.e. preliminary investigation) produced several notable relationships among predictor variables when using both a correlation matrix and scatter plots. The correlation matrix displayed in Table 2 produced several intuitive relationships. The Pearson correlation coefficient (i.e. $-1 \leq r \leq +1$) captured in Table 2, helped to assess both the strength and direction of the association between Revenue and its host independent variables. The numerical value quantified the strength of the association, whereby direction was noted by either a positive or negative sign.

Of particular concern in this study was the condition associated with multicollinearity, because it created instability and produced inflated standard errors in the regression model. The advertising (ADVEXP) variable exhibited this condition and was dropped from further consideration. Other observed relationships were noted below.

In general, seasonal variables (i.e. Fall, Win, Spring, Sum) exhibited a poor relationship with revenue. Summer ($r=0.104$) was the only period to produce a positive relationship; however, its overall association with revenue was rather weak. Fluctuating fuel prices throughout the year adversely affected travel plans, which could partially explain the weak relationship. If fuel prices remained consistently low during summer months, travel would have increased resulting in increased revenue for the rental car company. A strong positive correlation coefficient would have revealed this effect.

Overall, fiscal quarterly periods (QUAR1, QUAR2, QUAR3 and QUAR4) provided weak relationships. The second quarter relative to the others had the highest correlation ($r=0.128$) albeit weak. According to the rental company's operations manager, the trend had always been for increased budgeted planned travel by business travelers during this quarter. In addition, it was not a coincidence that

TABLE 2
CORRELATIONS: REV, FAL, WIN, SUM, QUAR1, QUAR2, QUAR3, REGION1, ...

	REV	FAL	WIN	SUM	QUAR1	QUAR2	QUAR3
FAL	-0.128						
	0.125						
WIN	-0.120	-0.333					
	0.151	0.000					
SUM	0.104	-0.333	-0.333				
	0.216	0.000	0.000				
QUAR1	-0.083	-0.333	0.556	0.111			
	0.321	0.000	0.000	0.185			
QUAR2	0.128	-0.333	-0.333	0.556	-0.333		
	0.128	0.000	0.000	0.000	0.000		
QUAR3	0.050	0.111	-0.333	-0.333	-0.333	-0.333	
	0.551	0.185	0.000	0.000	0.000	0.000	
Region1	-0.235	0.000	-0.000	-0.000	0.000	0.000	0.000
	0.005	1.000	1.000	1.000	1.000	1.000	1.000
Region2	-0.242	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	0.004	1.000	1.000	1.000	1.000	1.000	1.000
Region3	0.921	-0.000	0.000	0.000	-0.000	-0.000	0.000
	0.000	1.000	1.000	1.000	1.000	1.000	1.000
POPDAT	0.018	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	0.832	1.000	1.000	1.000	1.000	1.000	1.000
UNEMP	0.498	0.094	0.018	-0.217	-0.074	-0.138	0.108
	0.000	0.264	0.832	0.009	0.379	0.100	0.199
GASOL	0.032	0.099	-0.176	-0.016	-0.281	0.070	0.073
	0.704	0.236	0.035	0.848	0.001	0.407	0.384
NUMREN	0.929	-0.078	-0.128	0.075	-0.073	0.080	0.054
	0.000	0.355	0.125	0.371	0.386	0.338	0.518
RENDAY	0.986	-0.138	-0.083	0.107	-0.031	0.088	0.033
	0.000	0.100	0.321	0.202	0.714	0.294	0.697
AVEREN	-0.014	-0.106	0.116	0.055	0.111	0.009	-0.056
	0.871	0.208	0.165	0.516	0.184	0.916	0.506
REVPDAY	0.794	-0.097	-0.244	0.140	-0.256	0.283	0.078
	0.000	0.249	0.003	0.095	0.002	0.001	0.355
FLTSIZE	0.969	-0.155	-0.043	0.119	-0.023	0.135	-0.012
	0.000	0.063	0.608	0.155	0.785	0.106	0.886
UTLIZ	0.181	0.074	-0.039	-0.087	0.064	-0.161	0.088
	0.030	0.380	0.639	0.298	0.448	0.054	0.292
REVPUNIT	0.756	-0.025	-0.266	0.055	-0.195	0.064	0.170
	0.000	0.767	0.001	0.515	0.019	0.449	0.041
ADVEXP	1.000	-0.128	-0.120	0.104	-0.083	0.128	0.050
	*	0.125	0.151	0.216	0.321	0.128	0.551
CPI	0.023	0.154	-0.175	-0.068	-0.286	0.009	0.116
	0.787	0.066	0.036	0.420	0.001	0.914	0.167

consumers who received their tax returns frequently booked leisurely travel during this same period.

Region 3 (0.921) revealed a strong positive relationship. This result was expected because the rental car operator catered to numerous businesses. It helped that its office was located

in an industrial region, where Region 3 served a population of almost 100,000.

The correlation matrix above provided numerical values to help with interpreting relationships. Alternatively, scatterplots proved to be effective graphical tools for identifying non-linear relationships. Some common non-linear relationships include curvilinear (i.e.

FIGURE 2
UNEMPLOYMENT VS. REVENUE

FIGURE 3
NUMBER OF RENTALS VS. REVENUE

quadratic) and exponential forms. Several scatterplots presented below highlight the relationship between revenue and some of its predictor variables.

As shown in Figure 2, unemployment (UNEMP, $r=0.498$) yielded a curvilinear pattern. An inverse relationship was expected.

Higher unemployment should have resulted in fewer rentals thereby inversely influencing revenue. Unfortunately, this was not the case. The operations manager explained that rates were kept low to encourage increased rentals and to recognize that higher fuel rates would only serve to compound declining rental revenue. In fact, those who were unemployed could still make use of rentals to seek continued employment opportunities by taking advantage of lower rental rates.

Figure 3 depicted the number of rental units (NUMREN, $r=0.929$) which yielded a strong positive linear relationship with revenue.

Intuitively this behavioral pattern was expected. The rental operator indicated that it had aggressively focused on quicker turnaround times for getting its rental units back in service. This was particularly true during peak periods such as Thanksgiving. The rental car company also targeted businesses for repeat rentals by providing attractive reduced rates to secure long-term rental contracts.

Figure 4 illustrated a strong and positive linear association between revenue and the number of days rented (RENDAY, $r=0.986$).

The rental car operations manager indicated a preference to secure long-term rental contracts by providing attractive corporate discounts, which boosted rental revenues and increased utilization. For instance, businesses would often rent minivans to accommodate group travel to events such as conferences for their employees. These types of events can last for several days. The rental van would reduce group travel expenses by eliminating the need for taxi or any other shuttle service.

FIGURE 4
NUMBER OF RENTAL DAYS AND REVENUE

FIGURE 5
GASOL VS. REVENUE

The predictor variable, GASOL, illustrated in Figure 5, produced a random association when correlated with revenue ($r=0.032$).

An inverse relationship was expected, however, fluctuating prices in fuel did not influence revenue. In essence, it demonstrated that consumers and businesses acted randomly with regards to consumption of fuel. Businesses and consumers adjusted their travel plans to reflect changes in the price of fuel.

The model's four assumptions, 1) Zero mean, 2) Constant variance, 3) Normality and 4) Independence, were verified and validated using the residual plots from Minitab as shown in Figure 6.

The first residual plot (residual vs. fits) validated the zero mean and constant variance assumptions. In this plot, it can be seen that the zero mean condition was satisfied because the residuals were randomly scattered about the mean zero residual line. The constant variance condition was also satisfied because an estimated equal number of the residuals were

randomly situated above and below the mean zero residual line. The constant variance condition would have been violated if a cone shape or fan-like pattern had been detected. Both the normal probability and histogram plots satisfied the assumption of normality (Kutner, 2005 and Brandimarti, 2011).

The multivariate model shown in Table 3 was fitted during stage 3 of the model building algorithm.

The variance inflation factor (VIF) variable reduction methodology produced the best fit. The results for the final iteration were displayed by Minitab. These results were achieved after reaching two iterations where the resulting VIFs were all less than 3.0. A fitted model with independent variables displaying $VIFs < 3.0$ is highly acceptable in statistical modeling.

An F-test was conducted for the hypothesis shown in equation (6). The results were significant ($p=0.00$) at $\alpha=0.05$, which supported the existence of a relationship between revenue and its set of predictor variables.

FIGURE 6
PLOT

$$H_0: \beta_0 = \beta_1 = \beta_2 = \dots = \beta_{10} \dots \dots \dots (6)$$

According to the goodness-of-fit measure, with an $R\text{-sq} = 89.3\%$, the model provided an excellent fit to the data as shown in Figure 7. An estimated 10.7% of the total variation in monthly revenues remained unexplained. This can be attributed to the exogenous variables previously discussed, which described situations whereby businesses required their employees to car pool or encouraged them to use public transportation. Individual t-tests were conducted for each predictor variable with the results shown below (Rousseeuw and Van Zomeren, 1990).

The fall and winter seasonal variables were not favorable for the rental car business. Monthly revenues during fall declined by \$5,277 and \$625, respectively. Even though both periods observed a decline in monthly revenues, more individuals were prone to rent during the winter period relative to fall. Christmas may explain higher travel during this time. Revenues increased by \$6,869 during summer, which can be explained by increased vacation travel trips. Both fall and summer seasonal periods were significant at $\alpha=0.05$.

Region1 and Region 2 locations were significant at $\alpha=0.05$. Monthly revenues declined by \$25,655 and \$18,580, respectively. Region1 represented a smaller market for the rental car company. The rental car operations manager indicated that the company had to negotiate longer term rental contracts in order to remain profitable for small market locations, like Region1, which has a population of about 25,000. The location in Region2 was represented by a population of 195,000. A decline in revenue for Region2 was attributed to several business closures and relocation to another state.

The unemployment variable *UnEmp* was significant at $\alpha=0.05$. The sign on its coefficient was positive rather than negative indicating a positive relationship, which was not expected. It

TABLE 3
MULTIPLE REGRESSION ANALYSIS: REV VERSUS FAL, WIN, ...
(Output from Minitab)

The regression equation is									
REV = - 166222 - 5277 FAL - 625 WIN + 6869 SUM + 1005 QUAR1 - 595 QUAR2									
- 25655 Region1 - 18580 Region2 + 10163 UNEMP + 2634 REVPDAY + 46395 UTILIZ									
Predictor	Coef	SE Coef	T	P	VIF				
Constant	-166222	9578	-17.35	0.000					
FAL	-5277	1990	-2.65	0.009	1.823				
WIN	-625	2276	-0.27	0.784	2.385				
SUM	6869	2252	3.05	0.003	2.334				
QUAR1	1005	2247	0.45	0.656	2.324				
QUAR2	-595	2259	-0.26	0.792	2.348				
Region1	-25655	2446	-10.49	0.000	2.753				
Region2	-18580	1728	-10.75	0.000	1.374				
UNEMP	10162.9	926.5	10.97	0.000	2.810				
REVPDAY	2634.0	259.3	10.16	0.000	2.684				
UTILIZ	46395	9754	4.76	0.000	1.603				
S = 7659.70 R-Sq = 89.3% R-Sq(adj) = 88.5%									
Analysis of Variance									
Source	DF	SS	MS	F	P				
Regression	10	65154455491	6515445549	111.05	0.000				
Residual Error	133	7803237004	58670955						
Total	143	72957692495							

FIGURE 7
ACTUAL VS. PREDICTED MONTHLY REVENUES (2009-2011)

was possible that even those unemployed were still able to rent cars, because the rental car operator kept its rental rates affordable. With recessionary conditions and higher fuel prices, the rental car operator could ill afford to ground its fleet keeping higher rental rates and subsequently adversely affecting its utilization. Lower rental rates positively impact monthly revenues because it is affordable even for those seeking transportation means as they are job hunting.

Revenue per day (RevDay) and utilization (Util) were both significant at $\alpha=0.05$. Each day adds \$2,634 in revenue across its four locations. Increasing utilization from its fleet by one percent increased monthly revenue by \$46,395.

LIMITATIONS, RECOMMENDATIONS AND FUTURE WORK

This study would have benefited from a database encompassing more than three years to establish a stronger foundation for building a deterministic model, where, for example, trends could have been identified.

The database did not capture information about its mix of rental vehicles. The inclusion of vehicle mix (i.e. compact, midsize, full size, SUV and minivan) in the model building process would have enhanced the results. Rental revenues would have been impacted by both fleet size and mix of vehicles.

Customer demographics would have been helpful in identifying not only the impact on revenue, but also to target specific groups in their marketing campaign. For instance, identifying local vs. non local residents, age of customer, business vs. leisure travel needs, male vs. female, preferences in rental vehicle and so forth, would provide added benefits to further explain variation in rental revenues.

Profitability is impacted by both revenue and cost. Maintenance cost was captured in the database. This component would be vital

particularly because the rental companies were keeping their units in inventory longer. Increased maintenance costs would adversely impact revenue. For instance, units which required frequent repairs presented both business and safety risks.

CONCLUSION

Although the United States has been officially declared out of the recession, rental car companies still face significant changes in their business model in order to maintain expected profit margins. The recession's negative impact on the airline and travel industries also negatively impacted the rental car industry. After suffering large reductions in revenue during 2009 and 2010, the results from 2011 show slight increases in revenue, and flat to negative increases in repair and replacement costs for vehicles. The depreciation bonus was reduced to one half in 2012 and potentially required additional attention to maintaining rental fleets for longer periods of mileage and number of months held in the fleet.

The multivariate decision model developed in this article provides a tool with which decision-makers at rental car companies can optimize the use of their assets in order to maximize revenue. With this model, they will be able to perform "what-if" scenarios with predictor variables, which are significant to their monthly revenue streams. As with any statistical model, there will always be factors which cannot be quantified, such as policies adopted by businesses to promote public transportation or taxis in lieu of renting a vehicle.

The results from this model reveal significant findings which impact rental revenues. For instance, summer and fall seasonal periods had opposite effects on revenues. As expected, monthly revenues increased during the summer; however, sharp decreases were observed in the fall, which is likely the result of decreased travel. Management use information like that produced in the model to adjust marketing

strategies during periods like fall season when travel declines.

As with many businesses, location plays an important role in determining yield. The monthly revenues of two of the four car rental locations used in this study were adversely impacted by the predictor variables Region1 and Region2. Management can use this information to decide the degree to which it must implement changes to improve yield at these locations.

Survival in the “new economy” will continue to present challenges for U.S. rental car companies. The deterministic model presented in this article provided promising results in terms of helping decision-makers maximize revenue. Improvements to rental car companies’ databases will enhance the model’s predictive capability and provide management with a powerful supplemental decision-making tool.

REFERENCES

- Altman, R. and Helms, M. (1995), “Quantifying Service Quality: Case Study of A Rental Car Agency,” *Journal of the American Production and Inventory Control Society*, 36(2): 45-50.
- Antich, M. (2012), “*Fleet Car Maintenance Costs Remain Flat in 2011-CY*,” [On-line]. Available: <http://www.automotive-fleet.com/Channel/Maintenance/Article/Story/2012/03/Fleet-Car-Maintenance-Costs-Remain-Flat-in-2011-CY.aspx>
- Arcelus, F.J. and Srinivasan, G. (1998), “Ordering Policies Under One Time Only Discount And Price Sensitive Demand,” *IIE Transactions*, 30(11): 1057-1064.
- Auto Rental News (2012), “*Research and Statistics*,” [On-line]. Available: <http://www.autorentalnews.com/Content/Research-Statistics.aspx>.
- Brandimarte, P. (2011), “*Quantitative Methods*”, Wiley and Sons, Inc., Hoboken, NJ. (pp. 509-520).
- Belobaba, P. (1987), “Airline Yield Management an Overview of Seat Inventory Control,” *Transportation Science*, 21(2): 63-73.
- Cook, R. D. and Weisberg, S. (1985), “*Residuals and Influence in Regression*,” *Biometrical Journal*, 27(1): 80.
- Filliben, J. J. (1975), “The Probability Plot Correlation Coefficient Test for Normality,” *Technometrics*, 17 (1): 111-117.
- Department of Transportation (2012), “*Bureau of Transportation Statistics*,” [On-line]. Available: www.bts.gov.
- Gallego, G. and Van Ryzin, G. (1997), “A Multiproduct Dynamic Pricing Problem and Its Applications to Network Yield Management,” *Operations Research*, 45(1): 24-41.
- Kutner, M., Nachtsheim, C., et al. (2005), “*Applied Statistical Models*”, 5th ed., McGraw-Hill/Irwin. New York.
- Lin, F. (2008), “Solving Multicollinearity in The Process of Fitting Regression Model Using the Nested Estimate Procedure,” *Quality and Quantity*, 42(3): 417-426.
- O’Brien, R.,M. (2007), “A Caution Regarding Rules of Thumb for Variance Inflation Factors” *Quality and Quantity*, 41(5): 673-690.
- Pardoe, I. (2006), “*Applied Regression Modeling – A Business Approach*,” John Wiley and Sons, Hoboken, NJ.
- Rousseeuw, P. J. (1984), “Least Median of Squares Regression,” *Journal of the American Statistical Association*, 79: 871-880.

Rousseeuw, P. J. and Van Zomeren, B. C. (1990), "Unmasking Multivariate Outliers and Leverage Points," *Journal of the American Statistical Association*, 85(411): 633-639.

Smith Travel Research (2012), "*US Hotel Performance for September*," [On-line]. Available: "<http://www.calculatedriskblog.com/2012/06/hotels-occupancy-rate-close-to-pre.html>"

Towes, J. (2012), "*Gas Price Data*" [On-line]. Available: <http://www.gasbuddy.com>.

Weatherford, L. and Bodily, S. (1992), "A Taxonomy and Research Overview of Perishable-Asset Revenue Management: Yield Management, Overbooking, and Pricing," *Journal Operations Research*, 40(5): 831 – 844.

AUTHOR BIOGRAPHIES

Anthony Narsing is an Associate Professor of Management at Macon State College. He currently teaches operations management, business statistics and quantitative methods courses. Professor Narsing has been with Macon State College since 2004. His primary research areas of interest include linear programming, quality management, supply chain management and operations research. He has presented numerous articles at DSI, ASEM, SEDSI and POMS conferences. Some of his published articles have appeared in the *Journal of Applied Business Research*; *Journal of Business and Economics Research*; *Simulation*; and *Academy of Information and Management Sciences Journal*. E-Mail: anthony.narsing@maconstate.edu

Terry Sanders is an Assistant Professor of Management at Macon State. He currently teaches communication in the business environment, business information applications, and marketing promoting and communication. Professor Sanders has been with Macon State since 2004. His primary research areas of interest include RFID, software development and implementation strategies. He has presented articles at SEDSI, Academy of Strategic Management, Teaching Matters and Allied Academies conferences. Some of his published work has appeared in *Academy of Information and Management Sciences Journal*. He has extensive experience in custom software for the collision repair industry. E-Mail: terry.sanders@maconstate.edu

Len Kistner is an Assistant Professor of Marketing at Fort Valley State University. He currently teaches principles of marketing, international marketing, and marketing-not-for-profit organizations. Professor Kistner has been with Fort Valley State since 2009. His primary area of research includes new product development, international business, and distribution channels. He has presented articles both nationally and internationally. Some of his published works have appeared in *Industrial Marketing Management*. His career in industry includes 24 years of product marketing and general management in manufacturing environments, where he held positions as President/CEO and VP. E-Mail: kistnerl@fvsu.edu

Jerry Williams is a Lecturer in Management at Macon State College. He currently teaches purchasing and supply chain management, principles of management, collective bargaining and labor relations. Mr. Williams has been with Macon State since 2009. His primary area of research includes logistics, supply chain management and collective bargaining. He has presented articles at SEDSI and Teaching Matters conferences. He has over 20 years of experience working the field of logistics and supply chain management. He was the education and training leader for the Air Forces' Purchasing and Supply chain Management program. E-Mail: jerry.williams@maconstate.edu