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Airport Offsite Passenger Service Facilities: An Option for Improving Landside Access: Volume II: Access Characteristics and Travel Demand

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16. Abstract

Offsite airport facilities provide ground transportation, baggage and passenger check in, and other transportation services to departing air passengers from a remote location. The purpose of this study was to develop models to determine the airports that might be candidates for such a facility and estimate the percentage of travelers that would choose to use one to access the airport.

Offsite airport facility operations were examined in New York, Los Angeles, Zurich, London, and Hong Kong, and passenger data were obtained from surveys distributed at six U.S. airports. A total of 1,700 air-traveler questionnaires were completed at four airports without offsite facilities, i.e., Baltimore/Washington International Thurgood Marshall Airport (BWI), Charlottesville-Albemarle Airport (CHO), Norfolk International Airport (ORF), and Richmond International Airport (RIC), and at two airports with offsite facilities that provide ground transportation only, i.e., Boston Logan International Airport (BOS) and San Francisco International Airport (SFO). The survey results show that 68% of passengers who traveled directly to the airport terminal would consider using an offsite airport facility if available. Of the passengers who currently use an offsite airport facility that provides only ground transportation, almost 70% indicated that their access would be improved by expanded services including baggage and passenger check in. The two main reasons cited for using the offsite airport facilities surveyed in this study were reduced travel time variability (43%) and lower cost (39%).

With the data collected at the six airports, two models were developed sequentially to determine the demand for offsite facilities. The airport access quality model was used to establish initial demand by assuming that the likelihood of a viable offsite facility is directly proportional to the difficulty, or resistance, encountered during the current access trip to the airport. This model yielded expected results when tested with a former offsite airport facility. The offsite facility usage model was used to determine the probability of passengers using an offsite facility while accessing an airport and accurately estimated 58% of the test set responses.

The airport access quality model develops a value for total resistance and ranks the airports according to the current difficulty encountered by passengers during their access trip to the airport. When applied to three Virginia airports, passengers accessing RIC had the largest total resistance. Accordingly, RIC is considered to have the highest potential demand for an offsite facility.

The offsite airport facility usage model was based on flight departure time and variability in ground travel time as predictors of the final demand. For example, the model estimated an offsite airport facility demand of 74% for passengers departing between 8 and 10:30 A.M. when ground travel times vary by 45 min (rounded to the nearest 15-min interval). For passengers departing before 8:00 A.M. and with a ground travel time that varies by no more than 5 min, the models estimated demand at only 26%. The offsite airport facility usage model was also used to identify the zones (defined by zip codes) where potential use of offsite terminals is substantial.

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FINAL REPORT

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ABSTRACT

Offsite airport facilities provide ground transportation, baggage and passenger check in, and other transportation services to departing air passengers from a remote location. They were introduced in the United States in the 1950s but did not achieve widespread use. In recent years, interest has been revived in this airport access option because of changes in technology, land use, and air travel conditions. However, potential demand for new offsite terminals is not fully understood. The purpose of this study was to develop models for this research need, which is to determine the airports that might be candidates for an offsite facility and estimate the percentage of travelers that would choose an offsite facility to access the airport.

Offsite airport facility operations were examined in New York, Los Angeles, Zurich, London, and Hong Kong, and passenger data were obtained from surveys distributed at six U.S. airports. A total of 1,700 air-traveler questionnaires were completed at four airports without offsite facilities, i.e., Baltimore/Washington International Thurgood Marshall Airport (BWI), Charlottesville-Albemarle Airport (CHO), Norfolk International Airport (ORF), and Richmond International Airport (RIC), and at two airports with offsite facilities that provide ground transportation only, i.e., Boston Logan International Airport (BOS) and San Francisco International Airport (SFO). The survey results show that 68% of passengers who traveled directly to the airport terminal would consider using an offsite airport facility if available. Of the passengers who currently use an offsite airport facility that provides only ground transportation, almost 70% indicated that their access would be improved by expanded services including baggage and passenger check in. The two main reasons cited for using the offsite airport facilities surveyed in this study were reduced travel time variability (43%) and lower cost (39%).

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The airport access quality model develops a value for total resistance and ranks the airports according to the current difficulty encountered by passengers during their access trip to the airport. When applied to three Virginia airports, passengers accessing RIC had the largest total resistance. Accordingly, RIC is considered to have the highest potential demand for an offsite facility.

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INTRODUCTION

Options to improve the quality of airport landside access may include expanding existing terminals, widening access roads, constructing new parking facilities, adding curbside drop off/pick up areas (Shriner and Hoel, 1999), and providing operational enhancements such as the use of cell phone lots for drivers picking up passengers. Another option for improving airport landside access is an offsite airport passenger service facility, which serves an airport and its users by providing ground transportation to and from the main terminal, baggage handling, check in, and passenger information. A previous report (Volume I) (Goswami et al., 2008) provided information about the concept, history, and current operations of various types of offsite airport facilities. This report (Volume II) addresses how to estimate demand for offsite airport facilities.

Offsite facilities were first examined in the United States during the early 1950s (Mansel and Mandle, 2000). Most of the remote facilities that initially provided check-in service either have been vacated or serve only as limousine pick-up and drop-of points (Air Transport Association of America, 1976). Previous studies focused on determining a suitable location for such offsite facilities (Kanafani, 1971; Spliseth, 1971); determining the desirability of offsite facilities to improve airport access (Leder, 1970); analyzing the cost-effectiveness of offsite facilities as a means of relieving groundside congestion in major hub cities (Snell, 1971); and conducting a feasibility evaluation of the Marin Airporter offsite facility (Gosling and Novak, 1980). The last source (Gosling and Novak, 1980) estimated the proportion of passengers using an offsite facility based on the ratio of travel time directly to the airport and travel time using the offsite facility.

Increasing landside congestion at major airports has renewed interest in the use of offsite facilities (Gosling, 1987). Yet many of the previous studies evaluated offsite facilities that existed before1980. Since that time, passenger characteristics have changed (Goswami et al., 2008) and some offsite facilities have closed or modified their services (Berger, 1985; Gosling, 1994, 1997; Sebro, 2007). Through the use of models based on survey data collected at six U.S. airports, this study addressed the passenger demand for offsite facilities in the present context.

PROBLEM STATEMENT

One problem faced by transportation planners is that no modern methods to forecast demand for an airport offsite passenger service facility are available. Without such methods, offsite facilities will lack a process for evaluation and decision making, hindering applications that may be beneficial.

PURPOSE AND SCOPE

The purpose of this study was to develop, calibrate, and test an approach for estimating demand for airport offsite passenger service facilities. *Demand* was defined as the probability that passengers will choose to use an offsite facility. The approach was limited to passenger characteristics such as travel time to the airport, flight departure time (FDT), and the cost of the access trip. Factors other than passenger demand that could influence the viability of an offsite facility, such as the impact of airport parking revenue by introducing offsite terminals (Sherry, 2007), were beyond the scope of this study.

The study focused only on offsite airport facilities used by the departing air passenger, and data gathering efforts were limited to airports where permission to implement surveys was granted.

METHODOLOGY

Four tasks comprised the methodology:

1. A literature review identified suitable performance measures for offsite facilities.

2. Data were collected to determine departing air passenger characteristics.

3. The data from Task 2 and the variables identified in Task 1 were used to develop airport access quality models for use in forecasting airports that were likely candidates for locating an offsite facility.

4. The data from Task 2 were used to develop offsite facility usage models that estimate the percentage of passengers likely to use an offsite facility at a specific airport and to identify promising market segments.

Task 1: Identify Performance Measures for Facilities

The literature review was summarized in Volume I of this study (Goswami et al., 2008). Information about airport access was also obtained through web-based keyword searches, the WorldCat database, the VDOT Research Library, and libraries at the University of Virginia.

The results of the literature review were used to identify passenger performance measures that reflected passenger viewpoints rather than performance measures that reflect the viewpoints of airport owners or airlines. Examples of the former are (1) delay during the airport access trip (Mahmassani et al., 2002); (2) congestion at the curbside (Mahmassani et al., 2001); and (3) uncertain ground access times attributable to highway congestion (Cambridge Systematics Inc., 2004). Examples of performance measures that reflect the viewpoints of airport owners are the lack of landside access capacity (Ndoh and Ashford, 1993) and impacts on the environment (e.g., air emissions) (Airport Land Use Commission, 2005; Gray-Mullen, 2000).

Based on the metrics applicable to passengers, five quantifiable performance measures were selected that are likely to reflect the overall quality of the access trip and the percentage of passengers using an offsite airport facility.

Task 2: Determine Air Passenger Characteristics

Data Collection

Passenger travel data were obtained by a survey of departing passengers and direct observations at the following airports where permission had been granted:

1. Charlottesville-Albemarle Airport (CHO), Charlottesville, Virginia
2. Norfolk International Airport (ORF), Norfolk, Virginia
3. Baltimore/Washington International Thurgood Marshall Airport (BWI), Baltimore, Maryland
4. Richmond International Airport (RIC), Richmond, Virginia
5. Boston Logan International Airport (BOS), Boston, Massachusetts
6. San Francisco International Airport (SFO), San Francisco, California.

In Charlottesville, Norfolk, Baltimore, and Richmond, surveys were conducted within the airport terminal. A booth was established, and departing air passengers were requested to complete a survey (as shown in Appendix A). The surveys were conducted over a 2-day period in 2006 on the following dates: June 15 and 16 (CHO), June 26 and 27 (ORF), August 3 and 4 (RIC), and August 8 and September 8 (BWI).

At Boston and San Francisco, surveys were distributed on buses that provide transportation to the airport from different offsite airport facilities that provide ground transportation only (as shown in Appendix B). (Volume I of this study [Goswami et al., 2008} described seven categories of offsite facilities, and because BOS and SFO provide ground transportation only, they are classified as a Category VI facility as noted in Table 1 of Volume I.)

The BOS surveys were conducted September 18-19, 2006, and the SFO surveys were conducted February 5-7, 2007.

The surveys provided the following data:

- origin in the region (zip code)
- arrival time at airport
- scheduled flight departure time (FDT)
- ground travel time to airport
- perceived variability in ground travel time
- mode to access to airport
- cost of ground travel to the airport
- cost of flight ticket.

At Charlottesville, Norfolk, Baltimore, and Richmond, in addition to surveys, passenger processing times were collected manually at the terminal. At each airport, two or three data collectors were equipped with stop watches, data entry sheets, or a laptop and provided with a clear view of the queue and the check-in counter. Each data collector independently recorded the time a passenger entered the queue, the time the passenger reached the counter, and the time the passenger left the counter. Observations at each airport were made at different times in a day and at different check-in queues for a period of 2 days to identify the variation in processing times. Two data elements were collected: wait time in the queue prior to check in and service time at the check-in counter.

Average values of security checkpoint wait times were obtained from the Transportation Security Agency (TSA) website (TSA, 2007). Individual values could not be collected as permission was denied to collect data pertaining to security checkpoint times at the terminal.

Data Tabulation

The basis for survey tabulation of passenger time characteristics were based on the following elements as illustrated in Figure 1 (not to scale).

- *Pre-flight time:* time difference between when passengers leave for the airport and the scheduled boarding time

- *Flight time:* time difference between the airport scheduled departure and the scheduled arrival time at the destination airport

- *Destination airport travel time:* summation of pre-flight time and flight time

- *Ground travel time:* time taken to travel from origin to the airport terminal

- *Processing time:* summation of queue (waiting) time and service time at the check-in counter

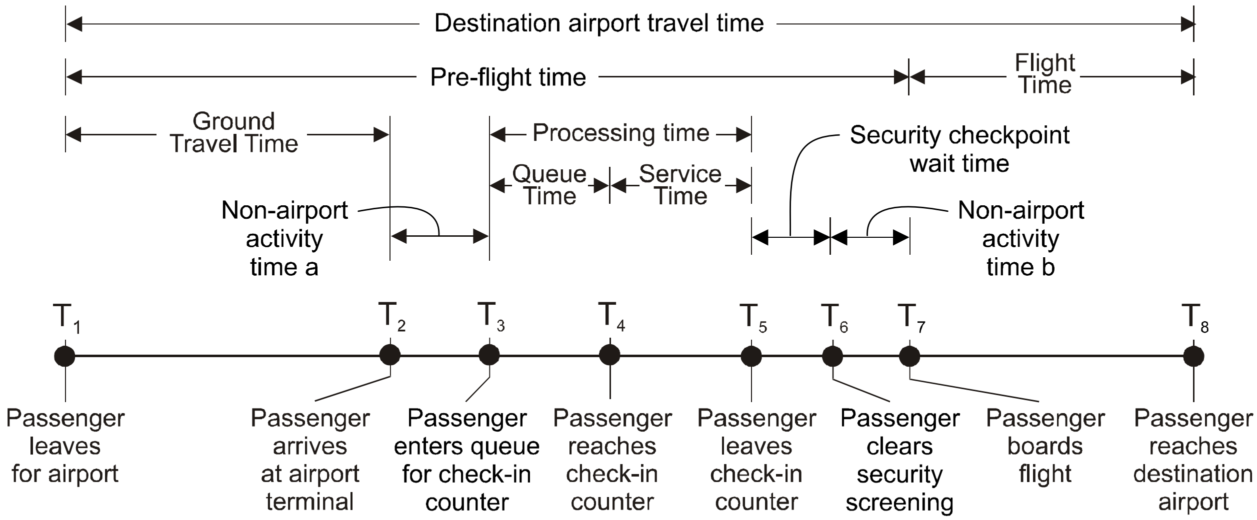

Figure 1. Components of Air Passengers' Destination Airport Travel Time

- *Non-airport activity time:* time spent at the terminal while not engaged in a specific airport/airline procedure

  – *Non-airport activity time = Non-airport activity time$_a$ + Non-airport activity time$_b$* (data pertaining to non-airport activity time$_a$ were not collected)

  – *Non-airport activity time$_a$*: time taken by the passenger to traverse from the terminal door to the check-in queue

  – *Non-airport activity time$_b$*: time spent by the passenger at the terminal after clearing security and prior to boarding the flight.

In addition to the average values and variation in these travel time components, three other types of information were extracted from the survey: passengers' willingness to use an offsite facility where none existed, passengers' reason for using the facility if one did exist, and originating zip code of the passenger. The zip codes served to identify areas with a high departing air passenger concentration.

Missing Data

The surveys were not always fully completed by respondents. Accordingly, a pairwise deletion process was used to address missing data as appropriate. For example, if a survey respondent provided ground travel time, distance to the airport, and access mode but omitted access cost, those computations that required the use of an access cost variable did not included this survey response. If, however, a regression analysis as described in Task 3 was performed where ground travel time was the dependent variable and access mode and distance from the airport were the independent variables, this response was included.

Task 3: Develop, Validate, and Apply Airport Access Quality Models

An airport access quality model quantifies the difficulty, or resistance, encountered by passengers en route to the airport. If the model indicates that the resistance to direct airport access is low, the airport is probably not a suitable candidate for an offsite facility. If the model indicates that the resistance to direct airport access is high, an offsite facility may potentially improve access. Thus, airport access quality models establish the possibility of demand by suggesting whether or not an airport offsite facility may be a promising option.

Development of Resistance Variables

Access resistance was measured using five resistance variables based on the performance measures identified in Task 1 impedance, access cost, ground travel time, processing time, and uncertainty (or ground travel time variability). Table 1 indicates how each resistance variable was obtained using the results of Task 2.

The sequence of steps used to develop airport access quality models were: (1) compute and validate the resistance variables, (2) apply the resistance function, and (3) validate the final airport access quality model.

Table 1. Resistance Variable Data Source

Resistance Variable	Source
Impedance	Inferred from question 9 from survey shown in Appendix A
Access cost	Question 8 from survey shown in Appendix A
Ground travel time	Question 3 from survey shown in Appendix A
Processing time	Summation of queue time and service time data collected at check-in counters at airport terminal
Uncertainty	Inferred from Questions 3 and 4 from survey shown in Appendix A

Compute and Validate Resistance Variables

For those situations where a survey is not feasible, it is necessary to estimate each variable from data that can easily be measured. For example, rather than asking respondents to provide a value for the "impedance" encountered during a specific trip, the value can be obtained from the ground travel time and the time the respondent left the place of origin (as will be shown in Eq. 11). If a relationship can be established between measured variables (e.g., ground travel time) and the five resistance variables, these relationships can be used to estimate similar variables at other airports where survey data are unavailable.

Accordingly, two approaches for estimating the five resistance variables were used: linear regression and cross classification. For each approach, a relationship was developed between the variables shown in Table 1 and independent variables that could more easily be measured. These relationships were based on 90% of the data collected. The relationships were then "tested" on the remaining 10% of the data to assess the ability of the independent variables to predict the resistance variables.

For example, for the linear regression approach, a relationship between the dependent variable, impedance, y_i, and the two independent variables, i.e., ground travel time and the time a respondent left the place of origin (x_1 and x_2), was developed based on 90% of the data. Then, the accuracy with which these relationships predicted the remaining 10% of impedances surveyed was determined.

Application of Resistance Function

The concept of the resistance function is derived from the notion of a desirability function developed by Derringer and Suich (1980), which states that the quality of a product with multiple quality characteristics is unacceptable if one of the characteristics lies outside the desired limits. For example, if the "product" is airport access and one of its characteristics is "ground travel time," the quality of airport access will be unacceptable if the ground travel time exceeds a predefined value, regardless of the value of other quality characteristics. This approach has been widely used for optimizing multiple-response problems (Castillo et al., 1996). The desirability function transforms each estimated response variable y_i to a desirability value d_i, such that the desirability values lie between 0 and 1. The value of d_i increases as the "desirability" of the corresponding response variable increases.

In an airport access application, an increase in a variable such as average access cost (y_i) will tend to reduce the desirability of this trip. In order to apply the desirability concept, the term *resistance* is used such that an increase in average access cost would be reflected by an increase the resistance encountered during the trip. In this case, the resistance value r_i increases as the corresponding resistance variable (y_i) increases.

The resistance function in Eq. 1 is used to transform the individual resistance variable (y_i) into a resistance value r_i.

$$r_i = \begin{cases} 0 & y_i \le y_{min} \\ \left(\frac{y_i - y_{min}}{y_{max} - y_{min}}\right)^z & y_{min} < y_i < y_{max} \\ 1 & y_i \ge y_{max} \end{cases} \qquad \text{(Eq. 1)}$$

Note that r_i is a function of y_i so that one could formally denote the resistance value as $r_i(y_i)$ rather than simply r_i. However, the nomenclature r_i is used in this report to distinguish the resistance value r_i from the resistance variable y_i.

Note also that the value of z in the superscript of Eq. 1 is specified by the user, where a large value of z is selected if the user wants y_i to increase rapidly above y_{min}. However, as will be discussed later in the context of Figure 5, a sensitivity analysis showed that z did not materially affect the study's results, and thus Eq. 1 used a value of z = 1.

The total resistance, R_{total}, of the passenger's access trip is given by the geometric mean of the individual resistance values (r_i) as shown in Eq. 2.

$$R_{total} = (r_1 \times r_2 \times ... \times r_k)^{1/k} \qquad \text{(Eq. 2)}$$

The total resistance does not give an absolute value but rather a relative value of the resistance of airport access. For example, if Airport A has a resistance of 0.29, it would be considered to reflect a lower difficulty in access compared to Airport B with a resistance of 0.42. As a consequence, Airport A would be a less likely candidate for an offsite airport facility than would Airport B.

Validation of Airport Access Quality Model

The East Side Airlines Terminal (ESAT) was used to validate the airport access quality model. Because the model development and calibration did not rely on ESAT data, the ESAT data represented a true test case where the prediction of the models could be compared to the actual performance of ESAT. Volume I of this report (Goswami et al., 2008) provides additional information about ESAT. Data were sought from persons familiar with ESAT, as one of the libraries that had reference materials was destroyed in the September 11, 2001 attack on the World Trade Center, and one source from the literature served as the basis for most of the ESAT data (Gosling et al., 1977).

Task 4: Develop, Validate, and Apply Offsite Facility Usage Models

An offsite facility usage model predicts the probability that passengers will use an offsite facility. An offsite facility usage model can also be used to identify offsite facility market segments or areas, identified by zip codes, where an offsite facility could be located.

Informally, a probability is the result that will transpire if a certain experiment is repeated an infinite number of times. Formally, this probability relies on the limit as the number of experiments approaches infinity (Ortúzar and Willumsen, 2004). If, for example, n_i is the number of times a given passenger chooses to use an offsite facility and n_o is the number of times the passenger chooses not to use an offsite facility, the probability of using an offsite facility P_i is given by Eq. 3, adapted from Ortúzar and Willumsen (2004).

$$P_i = \lim_{(n_i+n_o)\to\infty} \frac{n_i}{n_i + n_o} \qquad \text{(Eq. 3)}$$

In practice, the literature noted that although Eq. 3 presumes multiple experiments, the concept of probability may be extended to a single event (Hogg and Ledolter, 1992) such as the probability of a particular passenger using an offsite facility tomorrow. Whether multiple experiments or a single event is presumed, the basic laws of probability are constant (Hogg and Ledolter, 1992). For example, as per Eq. 3, p_i and p_o must sum to 1.0 if those are the only possible outcomes.

However, Eq. 3 suggests that one has greater confidence in seeing evidence of the probability as the total number of experiments $n = n_i + n_o$ grows larger. For example, if the probability of p_i is 0.412, if only one experiment is conducted ($n = 1$), the difference between the expected frequency ($p_i n = (0.412)(1) = 0.412$) and the observed frequency ($n_i = 0$ or 1) will be *at least* 0.412. If $n = 10$, then the difference between the expected frequency (4.12) and the observed frequency (0, 1, 2, 3, 4, 5, 6, 7, 8, 9, or 10) must be *at least* 0.12 (which would result if the observed frequency was 4). If n = 1,000, it is conceivable that the difference between the expected frequency (412) and the observed frequency (which could be 412) may be zero. Thus, for all probabilities computed in this study, one would expect a greater ability to see the expected frequency as the number of passengers to whom the probability is applied increases.

Model Development

One of the most common methods for predicting the probability of using a given mode, such as auto or transit, is the mode choice model (Garber and Hoel, 2009). For more than three decades, mode choice models have also been used to forecast the mode passengers will use to access an airport (Gosling, 2008). A particular modeling technique that appeared promising for this study was the binary logit regression model, which can be used to predict the probability of passengers using the offsite facility (Eq. 4).

$$E\{y\} = \Pr(Y = 1 \mid X = x) = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p)} \quad \text{(Eq. 4)}$$

This function can be generalized directly to a situation where there are p predictor variables, in vector β, i.e., β = $\beta_0, \beta_1, \ldots, \beta_p$. The reader should note that *E{y}* where Y = 1 is $P_{offsite}$ and that *E{y}* where Y = 0 is $P_{non\text{-}offsite}$. The ratio $\frac{P_{offsite}}{1 - P_{offsite}}$ is called the odds ratio for the event where

$$\frac{P_{offsite}}{1 - P_{offsite}} = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p) \quad \text{(Eq. 5)}$$

Eq. 4 may be derived by assuming that the utility of the offsite facility is given by Eqs. 6 and 7, where the vector **X** = 1 in Eq. 6 and X = 0 in Eq. 7.

$$U_{offsite} = \beta X = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \quad \text{(Eq. 6)}$$

$$U_{non-offsite} = \beta X = 0 \quad \text{(Eq. 7)}$$

Thus, the probability of using an offsite airport facility is given by Eq. 8,

$$P_{offsite} = \frac{\exp(U_{offsite})}{\exp(U_{non-offsite} + U_{offsite})} = \frac{\exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p)}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p)} \quad \text{(Eq. 8)}$$

and the probability of not using an offsite airport facility is given by Eq. 9.

$$P_{non-offsite} = \frac{\exp(U_{non-offsite})}{\exp(U_{non-offsite} + U_{offsite})} = \frac{1}{1 + \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p)} \quad \text{(Eq. 9)}$$

Dividing Eq. 8 by Eq. 9 and using the relationship $P_{offsite} + P_{non\text{-}offsite} = 1$ yields Eq. 5.

Taking the natural logarithm of both sides of Eq. 5 yields Eq. 10.

$$\ln\left(\frac{P_{offsite}}{1-P_{offsite}}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_p X_p \quad \text{(Eq. 10)}$$

The logarithm of the odds ratio as shown is called the logit, and the logit transformation produces a linear function of the parameters $\beta_0, \beta_1, \beta_2, ..., \beta_p$. The range of the values of $P_{offsite}$ is between 0 and 1, and the range of the values of $\ln(P_{offsite}/(1-P_{offsite}))$ is between $-\infty$ *and* ∞. Logistic regression fitting is carried out by working with the logits, and the method of estimation used is the maximum likelihood method.

As an alternative approach to that shown in Eqs. 4 through 10, a cross-classification model was also implemented.

Model Testing

As noted earlier, the relationships shown in Eqs. 4 through 10 were based on 90% of the data set. The models were tested by evaluating their prediction accuracy on the remaining 10% of the data set.

Model Application

The offsite facility usage model was used for two purposes:

1. *To predict the market segments that might be more likely to use an offsite facility at a given airport.* These market segments are based on the FDT and the variability in ground travel time.

2. *To identify promising zip codes for locating an offsite facility that would serve RIC and BWI.* The identification of such zip codes is based on the assumption that zip codes generating higher proportions of likely offsite facility users are the best candidate locations for an offsite facility. (RIC and BWI had been identified as airports that would be more conducive to an offsite facility than CHO and ORF based on the results of the airport access quality models used in Task 3.)

RESULTS AND DISCUSSION

Performance Measures for Offsite Airport Passenger Service Facilities

Volume I of this study (Goswami et al., 1908) suggested eight potential benefits of offsite airport facilities. Performance measures based on these benefits are given in Table 2. Some benefits apply only to the passenger (e.g., reduction in ground travel time), whereas other

Table 2. Performance Measures

Performance Variable[a]	Measurable Element[b]	Future Potential Benefit
Impedance	Satisfaction of access trip to airport and terminal operations	• Passenger satisfaction could improve from reduced baggage handling if allowed to check in at offsite facility • Services offered at offsite facilities could improve overall terminal efficiency, ultimately resulting in higher passenger satisfaction
Access cost ($)	Access cost, which includes parking costs, public transportation fare, tolls, and mileage	• Passengers could reduce parking costs by avoiding driving to airport and using public transportation from offsite facility
Ground travel time (min)	Time taken to travel from origin to airport terminal	• Reduction in ground travel time delay is possible as passengers would be use dedicated public transportation operating on HOV lanes from offsite facility to airport
Passenger processing time (min)	Check-in counter queue time and service time	• Passengers using offsite facilities could experience reduced delay at check-in counters
Uncertainty (min)	Perceived variation in ground travel time between origin and airport terminal	• Uncertainty could be reduced due to use of public transportation, which would be aided by modern technologies to adhere to strict schedules
Revenue and Land costs ($)	Revenue and land cost difference between airport expansion and using an offsite airport facility	• Offsite facility could act as substitute for expanding airport terminal and hence reduce demand for new land at airport site
Volume of automobiles (VMT)	CO, NOx, PM, and VOC emissions	• Use of public transportation by departing passengers might help in reducing emissions
Non-airport activity time (min)	Time spent by air passengers at airport terminal when not involved in required airline/airport activity	• Offsite facilities could offer increased amenities to passengers during waiting period • Terminal efficiency could be improved if space needed to hold passenger during non-airport activity time was used for other purposes such as check in, security, etc.

VMT = vehicle miles traveled; CO = carbon monoxide, NOx = nitrogen oxides, PM = particulate matter, VOC = volatile organic compound.
[a]The variable that would ideally be measured if data limitations did not exist (hence the ideal performance measure).
[b]The variable that is measured given existing data limitations (hence the performance measure used in this study).

benefits apply to the airport operator or airline owner (e.g., reduction in land costs) or the general public (e.g., reduction in emissions). The current study describes the process to determine passenger demand for offsite airport facilities,, and, accordingly, its focus was on the first five performance measures because they are direct indicators of passenger demand.

Air Passenger Characteristics

Figure 2 (drawn to scale) depicts travel components for an average passenger departing from BWI. The *destination airport travel time* denotes the length of the entire trip from the instant the passenger leaves his or her home or business to the moment the plane lands at the destination airport. Components of destination airport travel time include the time period during

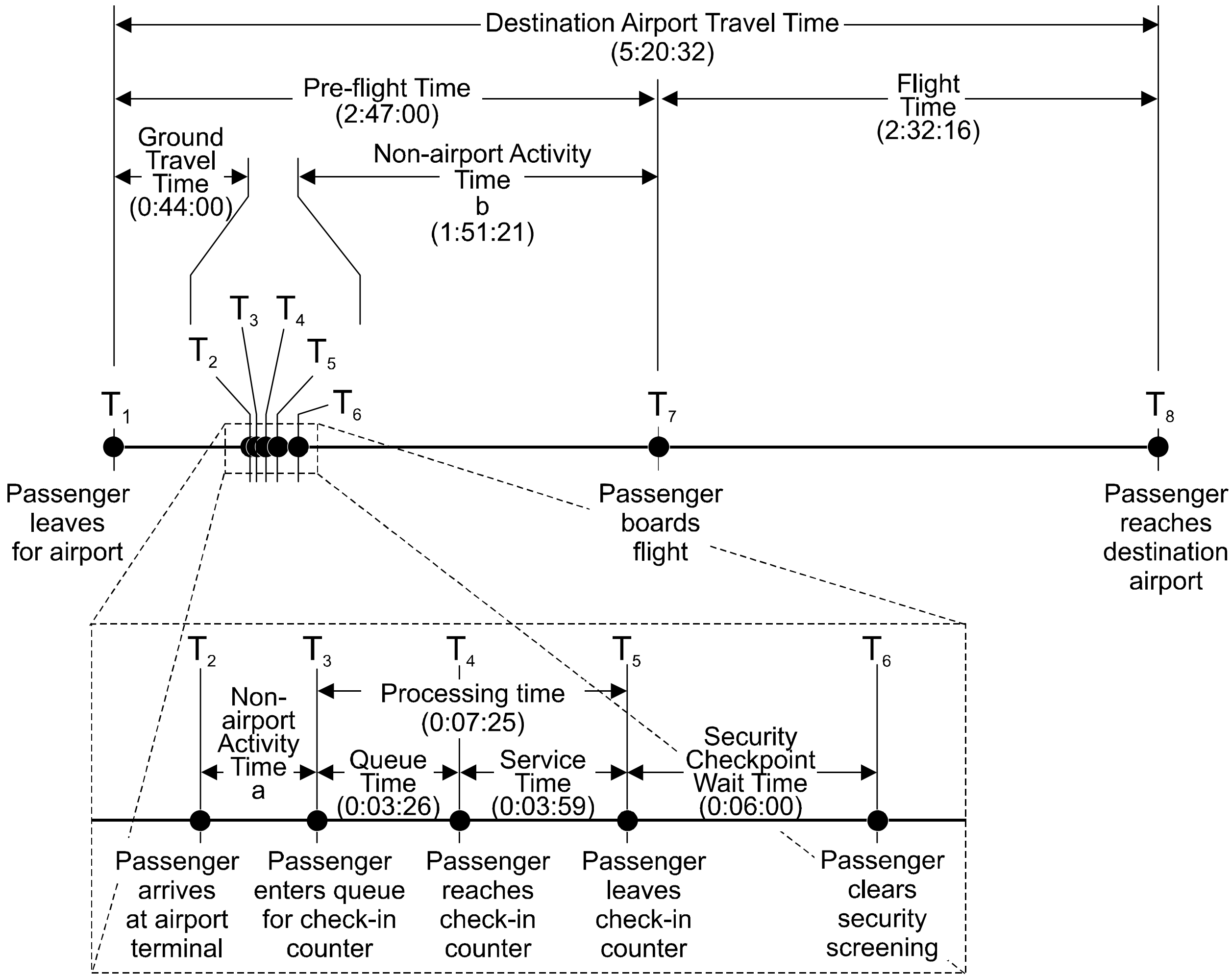

Figure 2. Travel Timeline of Passenger Departing from BWI

which the passenger travels by ground transportation to reach the airport (ground travel time), the time period during which the passenger spends waiting at the originating airport (non-airport activity time), and the time period where the plane is in the air (flight time).

The survey data describe average length for each travel time component in Figure 2, the variation in travel time for individual passengers, the passengers' willingness to use an offsite facility, and the passengers' zip code of origin.

Mean Travel Times

Table 3 summarizes the findings for two sets of passengers: those arriving directly at the airport, as was the case in Figure 2, and those using an offsite airport facility. The destination airport travel time varies between 4 hr 44 min (CHO) and 9 hr 02 min (SFO). The average flight time varied from 2 hr 32 min (BWI) to 5 hr 55 min (SFO), meaning that on average, the flight time was just 52% of the destination airport travel time.

Table 3. Summary of Survey Results

Parameter	CHO	ORF	RIC	BWI	Direct Access: Subtotal	Logan Express: Service to BOS	Marin Airporter: Service to SFO	Indirect Access: Subtotal	All Airports: Total
Average total processing time	4 min	12 min 31 sec	5 min 43 sec	7 min 25 sec	7 min 25 sec	*	*	*	
Average wait time at ticketing queues	1 min 24 sec	8 min 20 sec	2 min 3 sec	3 min 26 sec	3 min 48 sec	*	*	*	
Average service time at ticketing counters	2 min 36 sec	4 min 11 sec	3 min 40 sec	3 min 59 sec	3 min 37 sec	*	*	*	
Number of processing time observations	323	340	346	423	1,432	*	*	*	
Number of surveys collected	96	113	199	244	652	655	425	1,080	1,732
Average ground travel time to airport terminal	28 min	43 min	37 min	44 min	38 min	55 min	1 hr 32 min	74 min	50 min
Predominant mode of access	Auto (58%)	Auto (54%)	Auto (41%)	Auto (34%)	Auto (47%)	Drop off (52%)	Drop off (59%)	Drop off (56%)	
Second most predominant mode	Drop off (26%)	Drop off (21%)	Drop off (31%)	Drop off (24%)	Drop off (26%)	Auto (34%)	Auto (33%)	Auto (34%)	
Average arrival at airport prior to scheduled departure	1 hr 4 min	2 hr 22 min	2 hr 10 min	2 hr 2 min	1 hr 54 min	2 hr 10 min	1 hr 51 min	2 hr	1 hr 56 min
Average pre-flight time	1 hr 32 min	3 hr 3 min	2 hr 45 min	2 hr 47 min	2 hr 31 min	3 hr 37 min	2 hr 58 min	3 hr 17 min	2 hr 47 min
Average non-airport activity time	1 hr 2 min	2 hr 8 min	2 hr 03 min	1 hr 57 min	1 hr 47 min	*	*	*	
Average flight time	3 hr 12 min	2 hr 52 min	2 hr 40 min	2 hr 32 min	2 hr 49 min	3 hr 48 min	5 hr 55 min	4 hr 51 min	3 hr 29 min
Average ticket cost	$496	$465	$463	$376	$450	$439	$478	$459	$453
Average access cost	$38	$35	$37	$47	$39	$25	$29	$27	$35
Willing to use offsite facility	55%	66%	72%	70%	68%	74%	64%	70%	69%
Average destination airport travel time	4 hr 44 min	5 hr 52 min	5 hr 29 min	5 hr 20 min	5 hr 21 min	6 hr 44 min	9 hr 02 min	7 hr 53 min	6 hr 11 min
Average flight time vs. destination airport travel time	61%	47%	47%	46%	50%	52%	61%	57%	52%
Average ground travel time vs. destination airport travel time	11%	12%	12%	14%	12%	17%	19%	18%	14%
Average ground travel time vs. flight time	24%	38%	31%	41%	34%	36%	39%	38%	35%
Average non-airport activity time vs. flight time	55%	107%	114%	106%	96%	*	*	*	
Average non-airport activity time vs. destination airport travel time	27%	39%	43%	41%	38%	*	*	*	

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport, BOS = Boston Logan International Airport, SFO = San Francisco International Airport.

Thus, the time not spent in the air, i.e., the pre-flight time, is a substantial portion of the passenger's journey, with an average of 2 hr 47 min per airport. The largest component of this pre-flight time was non-airport activity time (with an average duration of 1 hr 47 min) followed by ground access time (with an average duration of 50 min). The processing time was relatively small (with an average duration of slightly more than 7 min).

Two differences between the airports without offsite facilities and with the offsite facilities are also noted. The ground travel time for airports with offsite facilities (average of 74 min) is greater than the ground travel time for airports without offsite facilities (average of 38 min). Passengers using the airports with offsite facilities had longer flights (average duration of 3 hr 29 min) compared to passengers who used airports without such facilities (average duration of 2 hr 49 min).

Variation in Travel Times

Table 3 summarizes average values for each travel time component. For example, the average passenger arrived 1 hr 56 min ahead of his or her scheduled departure time, but this average value masks variation in individual passengers: some passengers arrived 10 min prior to departure and some arrived 9 hr prior to departure. This section discusses the variation in airport arrival time, ground travel time, processing time at the check-in counters, security time, and non-airport activity time.

Variation in Airport Arrival Time

Table 3 showed the average *arrival at airport prior to scheduled departure*, which was calculated by subtracting the passenger's scheduled boarding time from the stated time of arrival at the terminal. Table 4 repeats this average value for each airport and shows the coefficient of variation. (The coefficient of variation is calculated as the standard deviation divided by the mean.) The lower coefficient of variation for BOS and SFO when compared to RIC, ORF, and BWI indicates that passengers' ground travel time is less variable at the two airports where an offsite facility exists (BOS and SFO) than at an airport where no such facility exists (BWI, ORF, and RIC). One possible explanation is the use of HOV lanes by the buses at BOS and SFO, which should reduce this variation, or uncertainty, in ground travel time. A different possible

Table 4. Arrival Time at Airport Prior to Scheduled Departure

Airport	Mean	Median	Coefficient of Variation
CHO	1 hr 4 min	1 hr	46%
ORF	2 hr 22 min	2 hr	66%
RIC	2 hr 10 min	1 hr 47 min	65%
BWI	2 hr 2 min	1 hr 45 min	54%
BOS	2 hr 12 min	2 hr 5 min	49%
SFO	1 hr 54 min	1 hr 48 min	45%

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport, BOS = Boston Logan International Airport, SFO = San Francisco International Airport.

explanation is the variation in congestion levels, which is supported by the fact that CHO has the second lowest coefficient of variation in Table 4, no HOV lanes, and likely the lowest level of traffic congestion of the six airports studied.

Variation in Ground Travel Time

When passengers are using an offsite facility, the ground travel time has three components: ground travel time from origin to the facility, transfer time at the facility, and ground travel time from the facility to the airport. For example, based on the data obtained from the survey (Appendix B) for the Marin Airporter offsite facility, Table 5 shows the mean and coefficient of variation for the first component: the ground travel time from the top five originating zip codes to the corresponding offsite facility serving SFO. Table 6 shows comparable information for the remaining two components: the transfer times at the offsite facility and the ground travel times from the offsite facility to SFO.

Table 5. Variability in Ground Travel Time from Origin to Marin Airporter Terminal

Marin Airporter Terminal Accessed at	Originating Zip Code	Ground Travel Time to Marin Airporter Terminal	
		Mean	Coefficient of Variation
San Rafael	94901	14 min 32 sec	91%
San Rafael	94903	11 min 31 sec	41%
Manzanita	94941	7 min 34 sec	49%
Larkspur	94904	18 min 50 sec	110%
Novato	94947	33 min 37 sec	91%

Table 6. Transfer Time and Ground Travel Time from Marin Airporter Terminal to San Francisco International Airport

Marin Airporter Terminal at	Transfer Time		Ground Travel Time to San Francisco	
	Mean	Coefficient of Variation	Mean	Coefficient of Variation
Novato	10 min 41 sec	60%	1hr 15 min	23%
San Rafael	12 min 20 sec	52%	54 min 14 sec	15%
Larkspur	14 min 3 sec	64%	52 min 38 sec	14%
Seminary Drive	10 min 30 sec	60%	45 min 47 sec	17%
Manzanita	10 min 20 sec	65%	48 min 17 sec	15%
Sausalito	14 min 12 sec	76%	44 min 16 sec	18%

Variation in Processing Time

Table 3 showed that the average time to process a passenger at the check-in counters was relatively low (e.g., 5 min 43 sec at RIC) compared to the other travel time components. Table 7 shows that these processing times were highly variable (e.g., a 90% coefficient of variation at RIC).

Variation in Security Time

The TSA provides the average, median, and maximum wait times of passengers at security gates for various airports (TSA, 2007). Table 8 shows that these average times are relatively low (e.g., a 2-min average at RIC). The reader should note the large deviation between

Table 7. Processing Time[a]

Airport	Mean	Median	Coefficient of Variation
CHO	4 min	3 min 5 sec	74%
ORF	12 min 31 sec	8 min 38 sec	104%
RIC	5 min 43 sec	3 min 50 sec	90%
BWI	7 min 25 sec	5 min 52 sec	71%

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport , RIC = Richmond International Airport, BWI = Baltimore/ Washington International Thurgood Marshall Airport.
[a]Processing time is the summation of queue time and service time at ticketing counters

Table 8. Security Checkpoint Wait Time

Airport	Average	Median	Maximum
CHO	4 min	4 min	10 min
ORF	5 min	4 min	21 min
RIC	2 min	2 min	12 min
BWI	6 min	5 min	28 min
BOS	4 min	3 min	36 min

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport, BOS = Boston Logan International Airport.

the average and maximum values; e.g., although the average wait time at BWI was 6 min, the maximum wait time was 28 min).

Variation in Non-Airport Activity Time

After completing the security screening process, passengers have additional time prior to boarding the flight. This non-airport activity time is not only comparable to the actual flight time but is also a major portion of the total pre-flight time. The two data elements used to calculate the non-airport activity time—processing time and arrival at airport prior to scheduled departure—were collected using different methods. Thus, a given passenger's processing time cannot be matched with his or her arrival at airport prior to departure. Hence the non-airport activity time was determined by simulating 50 combinations of linking the two data elements. Based on these simulations, the mean and median of non-airport activity times are shown in Table 9 (truncated to the lowest minute).

Willingness to Use an Offsite Facility

As shown in Appendices A and B, one survey question was whether airport passengers would be willing to use an offsite facility (for surveys conducted at BWO, CHO, ORF, and RIC, which were not served by an offsite facility) or whether passengers would be interested in additional services at their offsite facility (for surveys conducted at BOS and SFO, which were served by offsite facilities providing only transportation).

Table 9. Non-Airport Activity Time[a]

Airport	Mean	Median	Coefficient of Variation
CHO	1hr 1min[b]	57 min 17 sec	49%
ORF	2 hr 8 min	1 hr 50 min	75%
RIC	2 hr 2 min	1 hr 37 min	68%
BWI	1 hr 57 min	1 hr 42 min	57%

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport.
[a]Time spent by passengers at terminal while not engaged in required airport/airline procedure.
[b]*Example:* The 95% confidence interval showed that lower bound for CHO mean time was 1 hr 1min 35 sec and upper bound was 1 hr 1 min 45.5 sec. Thus, the truncated value 1 hr 1min is within this 95% confidence interval.

Surveys Conducted at Airports without Offsite Facilities

At the four airport terminals without an offsite facility, passengers were asked if they would be willing to use an offsite facility in the future, provided that the facility was suitably located and would provide check-in, baggage handling, and transfer to the airport. Overall, 68% of the passengers indicated they would use such a facility. Responses varied slightly by airport: 72% (RIC), 70% (BWI), 55% (CHO), and 66% (ORF) indicated they would use such a facility.

Surveys Conducted at Airports with Offsite Facilities

Passengers on buses transferring them from offsite facilities to BOS and SFO were asked if they would like to have check-in and baggage handling in the future. Of these passengers, 74% of passengers using the Logan Express service at BOS indicated that they were in favor of additional services at the existing locations, and 64% of the passengers using the Marin Airporter service to SFO indicated the same.

These passengers were also asked why they preferred to use the offsite airport facility rather than accessing the airport directly. Table 10 shows the reasons passengers gave for using the offsite facility. Of the 963 passengers surveyed, 183 (19%) indicated that the only reason for using the offsite facility was that it reduced the variability in ground travel time compared to accessing the airport directly. 45 passengers (5%) cited all four reasons for using the offsite facility: shorter travel time, lower cost, reduced uncertainty of ground travel time, and convenient parking. Overall, 418 passengers (43%) perceived that reduced variability was at least one of the reasons that they preferred to use the offsite facility.

Geographic Distribution of Passengers

Some areas of a region may contribute a disproportionately large share of airport passengers. For example, at RIC, passengers arrived from 84 zip codes, but 19% of the zip codes (16 zip codes) accounted for 50% of the passengers. At CHO, three zip codes accounted for 48% of the passengers. Table 11 shows the market share of the top three passenger-generating zip codes for each airport. Figure 3 and Figure 4 show the three zip codes in the Charlottesville-Albemarle region and in the Richmond metropolitan area that generate the highest number of passengers at CHO and RIC, respectively.

Table 10. Offsite Airport Facility Preference

No. of Passenger Responses	Shorter Travel Time	Lower Cost	Reduced Variability	Convenient Parking
183			√	
179		√		
134	√			
132				√
49			√	√
45	√	√	√	√
42		√		√
39		√	√	
39	√		√	
32	√			√
29	√	√	√	
18	√	√		
18	√		√	√
16		√	√	√
8	√	√		√
% of Total	34%	39%	43%[a]	36%

[a]The percentage of passengers indicating reduced variability as one of the reasons for using offsite facility was calculated in the following manner: 963 responses were obtained; 418 indicated reduced variability as one reason for using facility (e.g., for 183 respondents, reduced variability was only reason, for 49 respondents, reduced variability and convenient parking were each cited as a reason). The ratio of 418/963 is 43%.

Table 11. Passenger Origins in Region

Airport	Top 3 Passenger-Generating Zip Codes	Cumulative Market Share of Top 3 Zip Codes	% of Zip Codes Generating 50% of Passengers
CHO	22901, 22902, 22903	48%	15%
ORF	23454, 23321, 23060	17%	25%
RIC	23112, 23220, 23185	14%	19%
BWI	21401, 21212, 21044	9%	27%
BOS	01701, 02184, 01801	8%	16%
SFO	94901, 94903, 94941	32%	6%

CHO = Charlottesville-Albemarle Airport, ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport , BOS = Boston Logan International Airport, SFO = San Francisco International Airport.

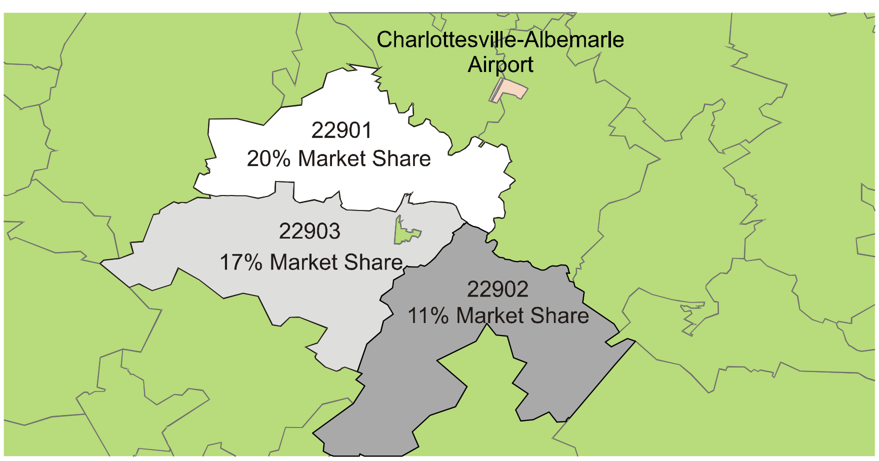

Figure 3. Top Three Passenger-Generating Zip Codes for Charlottesville-Albemarle Airport

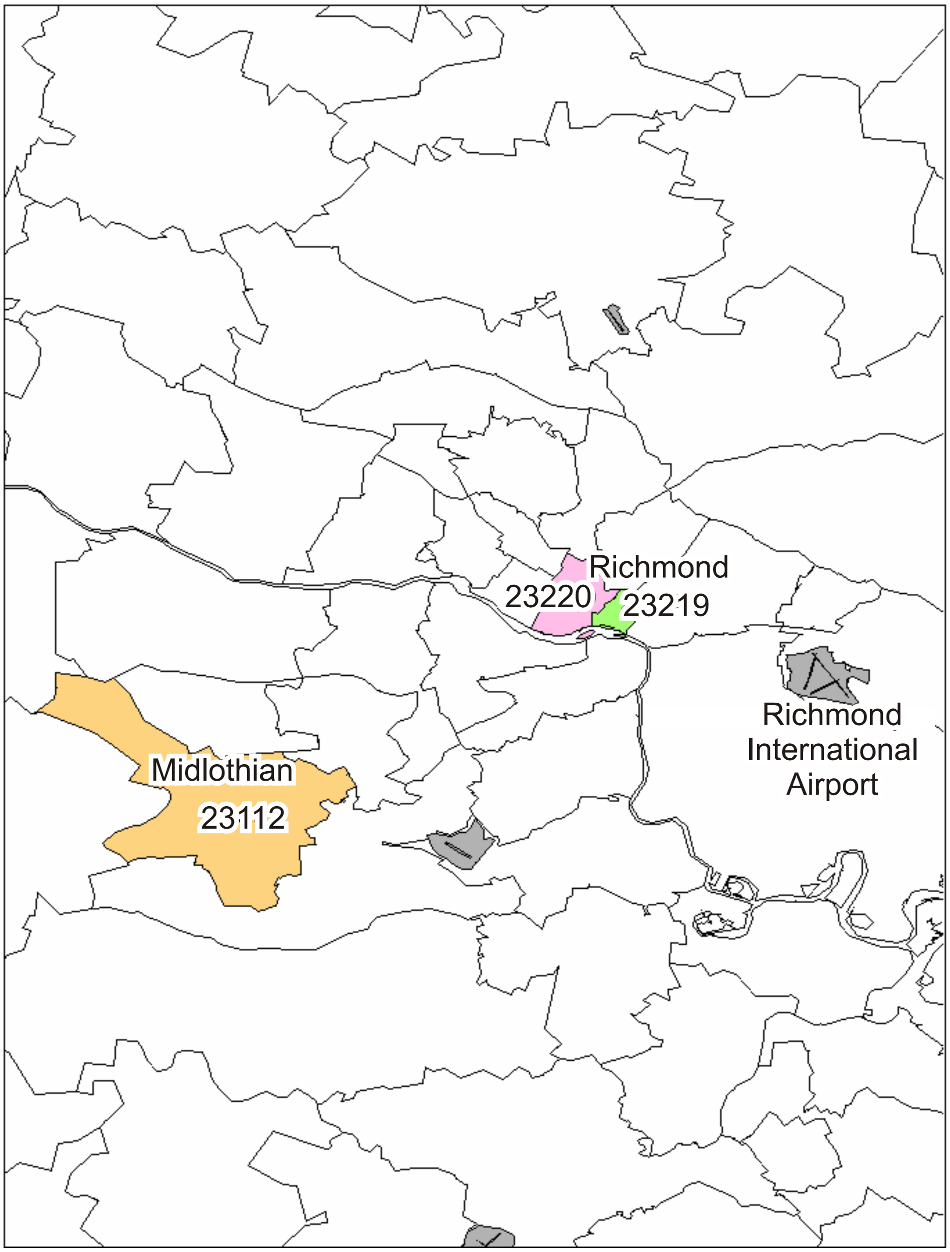

Figure 4. Top Three Passenger-Generating Zip Codes for Richmond International Airport

Development, Validation, and Application of Airport Access Quality Models

As discussed in the methodology for Task 3, airport access quality models are used to estimate the current difficulty experienced by passengers while accessing an airport. Airports that exhibit higher degree of difficulty, i.e., a higher resistance, suggested a higher initial demand for an offsite facility.

Because a reliable resistance function requires accurate resistance variables, a test was devised to ensure that the five variables are accurate. This test was as follows. Five hundred data points collected from four airports where passengers access the airport directly were randomly divided into two data sets: a training data set (90%) and a testing data set (10%). From the training data set, models were developed to determine each of the five resistance variables. Then, the accuracy of these models was determined with the test data set. This test determined whether linear regression or cross classification was more appropriate for estimating the resistance variables.

A final validation of the airport access model was performed by using data from ESAT.

Development of Resistance Variables Using Linear Regression

The five resistance variables were derived from the survey data as follows:

1. *Impedance*. The responses to Question 9 of the survey shown in Appendix A were used to code the impedance as follows: 1 (very satisfied and do not want improvements); 2 (satisfied, but expect improvements); 3 (not satisfied and want improvements).

2. *Access cost*. The responses to Question 8 of the survey were added to develop a single cost figure in units of dollars.

3. *Ground travel time*. The responses to Question 3 of the survey were used to develop a value in minutes.

4. *Processing time*. The summation of queue time and service time data collected at check-in counters at the airport terminal was used to estimate processing time in minutes.

5. *Uncertainty*. The responses to Question 3 gave the ground travel time as provided by passengers. The responses to Question 4 provide the origin of the travelers, which was, in turn, used to acquire the travel time as reported by Google, Inc. (2007). The absolute difference in minutes between this travel time and the ground travel time reported in Question 3 was used as a measure of uncertainty.

Computation of Resistance Variables

The regression equations for the five resistance variables are given in Eqs. 11 through 15.

Impedance, y_1 = 0.16(Ground travel time) + 0.016(Time left origin) + 1.25 (Eq. 11)

Access cost, y_2 = 0.15(Ground travel time) + 14.94(Taxi) – 14.33(Drop off) – 11.98(Bus) – 17.24(Rail) + 17.98 (Eq. 12)

Ground travel time, y_3 = 0.9(Distance from airport) – 25.29(Auto) – 27.24(Rental) – 29.17(Taxi) – 29.07(Drop off) – 25.29(Bus) + 39.61 (Eq. 13)

Processing time, y_4 = 1.02(Service time) + 0.018(Bags) + 0.04 (Eq. 14)

Uncertainty, y_5 = 0.23(Distance from airport) – 18.66(Auto) – 18.81(Rental) – 19.16(Taxi) – 18.71(Drop off) – 21.36(Bus) + 21.77 (Eq. 15)

The reader should note that time left origin shown in Eq. 11 was determined by subtracting ground travel time (Question 3, Appendix A) from time arrived at airport terminal (Question 2, Appendix A).

Eqs. 11 through 15 were developed based on the 90% training data set. The testing data set was then used to determine the accuracy of the predictions, and an absolute percentage error, defined as the difference between the predicted and true values divided by the true value. Eqs. 11 through 15 generally showed very high absolute percentage errors of 98%, 173%, 29%, 94%, and 174%, respectively.

Application of Resistance Function

The average values for the five resistance variables (from Eqs. 11 through 15) were transformed into resistance values (according to Eq. 1). For example, when data from BWI airport were used with Eq. 11 to determine y_{cost}, the maximum access cost predicted was $41.92, the minimum access cost paid predicted was $1.49, and the average cost paid by an air passenger accessing BWI as predicted by Eq. 11 was $21.36. Thus, the resistance value of the cost access variable for BWI is 0.49 based on Eq. 1.

$$r_{\cos t} = \left(\frac{Ave.\text{cost} - \min.\text{cost}}{Max.\text{cost} - \min.\text{cost}} \right) = \left(\frac{21.36 - 1.49}{41.92 - 1.49} \right) = 0.49 \, (z=1)$$

Similarly, the resistance values for the other four resistance variables were 0.28, 0.23, 0.18, and 0.24.

The total resistance for each airport was determined using Eq. 2. For example, the total resistance of an access trip to BWI is 0.27:

$$R_{\text{total,BWI}} = \left(\sqrt[5]{(r_{\text{cost}} * r_{\text{processing time}} * r_{\text{ground travel time}} * r_{\text{impedance}} * r_{\text{uncertainty}})} \right) = \left(\sqrt[5]{0.49 * 0.28 * 0.23 * 0.18 * 0.24} \right) = 0.27$$

Table 12 shows the components of the total resistance calculation for BWI. Table 13 shows the total resistance calculations for the remaining three airports. The results contradict the resistance function assumption: the assumption is that an increase in average values of a resistance variable should increase the resistance value. For example, the average ground travel time at CHO is 29 min and at BWI is 44 min. Accordingly, the ground travel time resistance value at BWI (0.23 in Table 12) should be higher than that of CHO (0.37 in Table 13). Clearly this is not the case. This contradiction, coupled with the large percentage errors that were observed when testing these data, suggests that the regression technique may not be appropriate for determining resistance variables.

The correlations among independent variables in Eqs. 11 through 15 and the correlation among the resistance values (e.g., r_{cost}, $r_{processing\ time}$, $r_{ground\ travel\ time}$, $r_{impedance}$, and $r_{uncertainty}$) were investigated to determine why the model gave contradictory results. Low correlation coefficients

Table 12. Resistance of Accessing Baltimore/Washington International Thurgood Marshall Airport

Predicted Resistance Variables (Eqs. 11-15)			Resistance Values (Eq. 1)	Total Resistance (Eq. 2)
Impedance	Max	2.32		0.27
	Min	1.44	0.18	
	Average	1.60		
Access cost	Max	$41.92		
	Min	$1.49	0.49	
	Average	$21.36		
Ground travel time	Max	140		
	Min	14	0.23	
	Average	44		
Processing time	Max	0.329		
	Min	0.042	0.28	
	Average	0.124		
Uncertainty	Max	35.00		
	Min	4.00	0.24	
	Average	12.00		

were found among the five resistance values, with all correlation coefficients below 0.15. Some degree of correlation, however, was found in two cases. Moderate correlation existed between ground travel time and time left origin (-0.3), which are the independent variables predicting impedance (Eq. 11), and between service time and number of bags (0.4), which are independent variables predicting processing time (Eq. 14).

Eq. 1 suggests that different values of z might affect the resistance function. Thus, a sensitivity analysis was performed with values of z not equal to the previously assumed value of $z = 1$. Figure 5 shows that varying the value of z between 0.1 and 3.0 does not affect the airport ranking in terms of resistance but it does affect the magnitude of the difference between airports.

Development of Resistance Variables Using Cross Classification

Unlike linear regression, which assumes residuals are normally distributed, cross-classification is nonparametric since no distribution is assumed. Further, cross classification does not require a linear relationship across all values of an independent variable. For example, cross classification might be advantageous if a small increase in ground travel time greatly increases impedance (Eq. 11) for some ground travel time below a certain threshold but has little effect for ground travel time above this threshold. As with the linear regression approach, five resistance variables were determined for use with Eq. 2.

Computation of Resistance Variables

As an illustration, one resistance variable may be considered, e.g., impedance. As was the case with the linear regression model, passenger satisfaction as reported in the survey was used to develop the impedance. The two independent variables that predict this impedance, *time left origin* and *ground travel time* are divided into categories. Table 14 shows the number of

Table 13. Resistance of Access Trip

Airport	Predicted Resistance Variables (y_i)			Resistance Values (r_i)	Total Resistance (R_{total})
CHO	Impedance	Max	1.66		0.32
		Min	1.36	0.37	
		Average	1.47		
	Access cost	Max	$35.98		
		Min	$4.30	0.44	
		Average	$18.17		
	Ground travel time	Max	56.78		
		Min	12.72	0.37	
		Average	28.98		
	Processing time	Max	0.321		
		Min	0.051	0.21	
		Average	0.109		
	Uncertainty	Max	26		
		Min	1	0.25	
		Average	8		
RIC	Impedance	Max	1.02		0.25
		Min	0.16	0.19	
		Average	0.32		
	Access cost	Max	$43.42		
		Min	$4.30	0.36	
		Average	$18.51		
	Ground travel time	Max	133.12		
		Min	14.14	0.22	
		Average	39.80		
	Processing time	Max	0.38		
		Min	0.04	0.25	
		Average	0.13		
	Uncertainty	Max	33.00		
		Min	2.00	0.26	
		Average	10.00		
ORF	Impedance	Max	1.78		0.28
		Min	1.41	0.37	
		Average	1.55		
	Access cost	Max	$45		
		Min	$5	0.39	
		Average	$20		
	Ground travel time	Max	149		
		Min	12	0.18	
		Average	37		
	Processing time	Max	0.239		
		Min	0.049	0.39	
		Average	0.123		
	Uncertainty	Max	38.00		
		Min	4.00	0.16	
		Average	9.00		

CHO = Charlottesville-Albemarle Airport, RIC = Richmond International Airport, ORF = Norfolk International Airport.

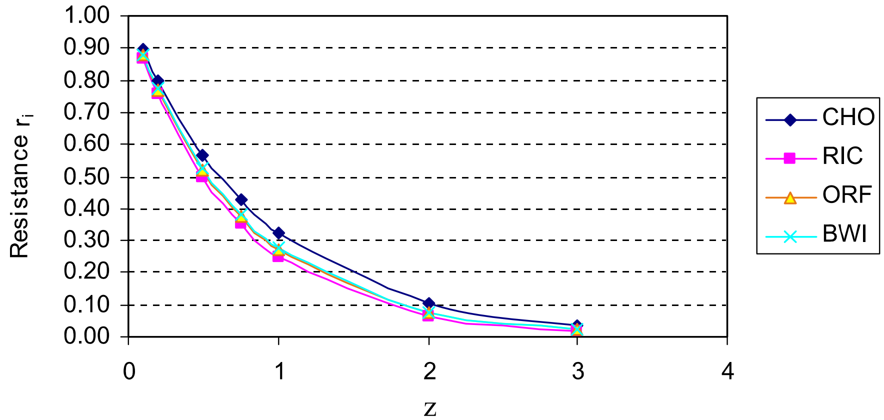

Figure 5. Effect of *z* on Resistance Values (r_i) (see Eq. 1)

passengers in each category. For example, there are 39 passengers whose ground travel time from their point of origin to the airport terminal was between 15 and 30 min and they departed from their point of origin between 9 A.M. and 12 P.M. The collective satisfaction of these passengers is 53 based on the survey responses. Based on these two numbers from Table 14, the impedance per person (=1.36) is calculated, as shown in Table 15, by dividing the collective satisfaction score (=53) by the number of passengers in the corresponding category (=39).

The impedances may be applied to the testing data set. Table 16 compares the predicted values to the actual values and shows that the average absolute percentage error is 13.39% for the impedance resistance variable.

Cross classification tables analogous to Table 15 were developed for the other four resistance variables: access cost (Table 17), ground travel time (Table 18), processing time (Table 19), and uncertainty (Table 20).

The absolute percentage errors are 30.85%, 13.80%, 16.66%, and 38.31%, respectively, for access cost, ground travel time, processing time, and uncertainty. Thus, computing the five resistance variables by the cross-classification method (Tables 15, 17, 18, 19, and 20) yields lower errors than those obtained from computation of the resistance variables by the linear regression method (Eqs. 11 through 15).

Application of Resistance Function

The five resistance variables from Tables 15, 17, 18, 19, and 20 may then be used with Eqs. 1 and 2 to determine total resistance of the access trip to each airport. For example, ground travel time can be considered. Table 18 showed that the minimum ground travel time was 14.58 min and the maximum ground travel time was 85 min. Using the data in Table 18 and Table 21, the average ground travel time for passengers accessing RIC is 40.04 min.

Table 14. Impedance Versus Time Left Origin and Ground Travel Time

Ground Travel Time (min)	Time Left Origin									
	Prior to 6 A.M.		6 A.M.-9 A.M.		9 A.M.-12 P.M.		12 P.M.-3 P.M.		3 P.M. or Later	
	Passengers	Satisfaction	Passengers	Satisfaction	Passengers	Satisfaction	Passengers	Satisfaction	Passengers	Satisfaction
<15	5	8	12	15	16	20	5	6	5	5
15-30	19	26	34	46	39	53	48	72	10	18
30-45	13	22	39	57	44	64	46	73	16	25
>45	9	14	47	68	48	79	49	85	1	3

Table 15. Impedance

Ground Travel Time (min)	Time Left Origin				
	<6 A.M.	6-9 A.M.	9-12 P.M.	12-3 P.M.	>3 P.M.
<15	1.60	1.25	1.25	1.20	1.00
15-30	1.37	1.35	1.36	1.50	1.80
30-45	1.69	1.46	1.45	1.59	1.56
>45	1.56	1.45	1.65	1.73	3.00

Table 16. Actual vs. Predicted Impedance

Ground Travel Time (min)	Time Left Origin									
	<6 A.M.		6-9 A.M.		9 A.M.-12P.M.		12-3 P.M.		>3 P.M.	
	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
<15	1	1.6	1	1.25	0	0	2	2.4	0	0
15-30	4	4.11	20	14.88	7	6.79	26	21	0	0
30-45	6	5.08	4	4.38	5	4.36	19	14.28	0	0
>45	6	4.67	4	4.34	5	4.94	19	15.61	0	0

Table 17. Access Cost

Ground Travel Time (min)	Ground Travel Mode		
	Auto	Drop-off	Other
<20	$13.93	$3.26	$16.62
20-30	$19.20	$5.97	$28.61
30-40	$22.01	$5.42	$29.00
40-50	$28.85	$7.53	$14.54
>50	$31.98	$12.13	$27.41

Table 18. Ground Travel Time

Distance from Airport (mi)	Ground Travel Mode		
	Auto	Drop-off	Other
<10	18.50	14.76	14.58
10-20	29.05	23.49	25.00
20-30	34.83	30.95	31.94
30-40	45.21	46.25	64.29
40-50	55.00	54.29	60.83
>50	84.31	85.00	65.63

Table 19. Processing Time

Service Time (hr)	No. of Bags		
	0	1	2+
<0.017	0.046	0.072	0.042
0.017-0.05	0.055	0.095	0.096
0.05-0.083	0.077	0.109	0.133
0.083-0.117	0.125	0.153	0.168
0.117-0.15	0.175	0.227	0.229
>0.15	0.170	0.200	0.233

Table 20. Uncertainty

Distance from Airport (mi)	Ground Travel Mode		
	Auto	Drop-off	Other
<10	4.94	3.26	4.90
10-20	7.03	6.40	6.27
20-30	6.40	5.30	6.67
30-40	7.92	6.90	7.11
40-50	7.28	10.88	8.80
>50	9.88	11.00	9.78

Table 21. Passenger Count

Distance from Airport (miles)	Ground Travel Mode		
	Auto	Drop-off	Other
<10	1	5	2
10-20	16	18	12
20-30	28	20	9
30-40	5	0	0
40-50	5	5	1
>50	15	6	5

Corresponding cells from Tables 18 and 21 are multiplied and average value of cells is calculated to determine average ground travel time of 40.04 min for passengers accessing Richmond International Airport.

Eq. 1 indicates the corresponding resistance for ground travel time for RIC is 0.36:

$$r_{\text{ground travel time}} = \frac{(40.04 - 14.58)}{(85 - 14.58)} = 0.36$$

The resistance values of the other four resistance variables were calculated in a similar fashion. Thus, the total resistance in passengers' access to RIC is the geometric sum of the resistance values based on Eq. 2, which is 0.38.

$$R_{\text{total,RIC}} = \sqrt[5]{(r_{\text{cost}} * r_{\text{processing time}} * r_{\text{ground trvel time}} * r_{\text{impedance}} * r_{\text{uncertainty}})} = \sqrt[5]{(0.49 * 0.37 * 0.36 * 0.24 * 0.52)} = 0.38$$

The total resistance of the other three airports is 0.29 (CHO); 0.42 (BWI); and 0.36 (ORF).

Thus, the cross-classification technique suggests that CHO has a lower resistance, and hence a lower difficulty of access, when compared to the other three airports. This, in turn, indicates that an offsite airport facility would be least viable for CHO. Use of the cross-classification technique, contrary to using the linear regression technique, supports the resistance function assumption: an increase in average values of a resistance variable increases the resistance value (as shown in Appendix C). For example, airports with larger average ground travel times (using Table 18), would have a larger value of $r_{\text{ground travel time}}$ (Eq. 1). Appendix C shows the resistance values of the resistance variables and the corresponding total resistance of the access trip to the different airports.

Table 22 shows the resistance of the access trips as determined by the two techniques. Based on the high absolute percentage errors for the linear regression technique (see Table 23), the cross-classification approach is the preferred technique for estimating the resistance variables needed for Eq. 2.

Model Validation: Test with East Side Airlines Terminal

A limited validation effort was conducting using information obtained from ESAT. Tables 24 and 25 contrast 2 years of ESAT operations 1970, when ESAT provided check-in services and the minimum fare for travel from ESAT to the John F. Kennedy International Airport (JFK) was $2.50, and 1976 when check-in services were no longer available and the

Table 22. Total Resistance Based on Airport Access Quality Model

Airport	Technique for Determining Resistance Variables	
	Regression	Cross-classification
CHO	0.32	0.29
ORF	0.28	0.36
RIC	0.25	0.38
BWI	0.23	0.42
Comment	Contradicts resistance function assumption[a]	Supports resistance function assumption

CHO = Charlottesville-Albemarle Airport; ORF = Norfolk International Airport, RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport.

[a]A higher resistance suggests higher difficulty of access trip. As it is believed that CHO access trip has lower difficulty than BWI access trip, results of regression-based airport access model contradict this belief.

Table 23. Absolute Percentage Error

Resistance Variable	Technique for Determining Resistance Variables	
	Regression	Cross-classification
Impedance	98%	13%
Access cost	173%	31%
Ground travel time	29%	14%
Processing time	94%	17%
Uncertainty	174%	38%

Table 24. East Side Airline Terminal (ESAT) Operations in 1970

Resistance variable	y_{avg}	Data Source
Impedance	1.2	Average impedance of 1.2 was inferred based on scale of satisfaction per Question 9 in Appendix A (1 = very satisfied, 2 = satisfied, 3 = not satisfied) and services available at ESAT, i.e., check in and transportation
Access cost ($)	5.0	Average access cost of $5 was inferred based on minimum cost of $2.50 charged from each passenger from ESAT to JFK plus additional cost of $2.50 was assumed, which passengers might have incurred while traveling from origin to ESAT
Ground travel time (min)	35	Average ground travel time of 35 min was inferred based on distance (=15 miles) between ESAT from JFK plus assumed average distance of 20 mi between ESAT at passenger origin (assumed travel speed of 60 mph)
Processing time (hr)	0.08	Average processing time of 0.08 hr was assumed based on current processing times at airports, which is 0.11 hr
Uncertainty (min)	4.5	Average uncertainty of 4.5 was inferred based on the Roadway Congestion Index (RCI) as reported by Texas Transportation Institute (Schrank and Lomax, 2007) (1.21 for Baltimore region and 1.13 for New York area in 2007) and average uncertainty of passengers accessing BWI according to Appendix C (7.23). RCI of 0.75 was extrapolated for 1970 (Wells, 2006) (RCI = 1 means that typical commute time is not more than 25% longer than off-peak travel time)

JFK = John F. Kennedy International Airport; BWI = Baltimore/Washington International Thurgood Marshall Airport.

minimum fare was $4.00 (Gosling et al., 1977). In the absence of individual data, all of the average values were inferred as noted in Tables 24 and 25. In addition, it was assumed that ground travel time and processing time remained unchanged and that the impedance increased from 1970 to 1976. Uncertainty values were calculated by extrapolating Roadway Congestion Index (RCI) values (Schrank and Lomax, 2007).

Table 25. East Side Airline Terminal (ESAT) Operations in 1976

Resistance Variable	y_{avg}	Data Source
Impedance	1.5	Average impedance of 1.5 was inferred based on scale of satisfaction per Question 9 in Appendix A (1 = very satisfied, 2 = satisfied, 3 = not satisfied) and services available at ESAT, i.e., transportation (check in discontinued) and hence lower satisfaction as compared to 1970
Access cost (dollar)	8.0	Average access cost of $8.00 was inferred based on minimum cost of $4 charged from each passenger from ESAT to JFK plus additional cost of $4 was assumed, which passengers might have incurred while traveling from origin to ESAT
Ground travel time (min)	35	Average ground travel time of 35 min was inferred based on distance (=15 mi) between ESAT from JFK plus assumed average distance of 20 mi between ESAT at passenger origin (assumed travel speed of 60 mph)
Processing time (hour)	0.08	Average processing time of 0.08 hr was assumed based on current processing times at airports, which is 0.11 hr
Uncertainty (min)	4.7	Average uncertainty of 4.7 was inferred based on Roadway Congestion Index (RCI) as reported by Texas Transportation Institute (Schrank and Lomax, 2007) (1.21 for Baltimore region and 1.13 for New York area in 2007) and average uncertainty of passengers accessing BWI according to Appendix C (7.23). An RCI of 0.77 was extrapolated for 1970 (Wells, 2006) (RCI = 1 means that typical commute time is not more than 25% longer than off-peak travel time)

JFK = John F. Kennedy International Airport; BWI = Baltimore/Washington International Thurgood Marshall Airport.

Tables 26 and 27 give the results of the cross-classification model based on the independent variables in Tables 24 and 25.

Since higher values for resistance signify a greater difficulty in access trip, the increase in resistance from 0.15 (Table 26) to 0.22 (Table 27) indicates that the model performed as expected: the increase in access cost coupled with the cessation of check-in services increased the difficulty of the trip. This finding is supported by a decline in the number of passengers using ESAT between 1970 and 1976 from 1.37 million passengers to 1.2 million passengers (Gosling et al., 1977). The literature examined in this report (Castillo et al., 1996; Derringer and Suich, 1980; Harrington, 1965) does not provide a method that can be used to determine whether differences in resistance, such as the 0.15 and 0.22 described here, are statistically significant.

Table 26. East Side Airline Terminal (ESAT) Resistance in 1970

Individual Resistance Values		Total Resistance
$r_{impedance}$	0.1	$R_{total,ESAT}$ = 0.15
r_{cost}	0.06	
$r_{ground\ travel\ time}$	0.29	
$r_{processing\ time}$	0.2	
$r_{unceratainty}$	0.19	

Table 27. East Side Airline Terminal (ESAT) Resistance in 1976

Individual Resistance Values		Total Resistance
$r_{impedance}$	0.25	$R_{total,ESAT}$ = 0.22
r_{cost}	0.17	
$r_{ground\ travel\ time}$	0.29	
$r_{processing\ time}$	0.2	
$r_{uncertainty}$	0.21	

Model Application: Selection of Promising Airports for Offsite Facility

The airport access models developed in this study may be used to identify candidate locations for an offsite facility. For example, because BWI and RIC have a higher resistance of airport access when compared to ORF and CHO, they are deemed candidate airports that could benefit from an offsite airport facility more so than ORF and CHO.

Development, Validation, and Application of Offsite Facility Usage Models

Two types of models were used to predict usage for offsite facilities: a binary logit model and a cross-classification model. Although some differences were noted, these models yielded similar levels of accuracy. The models were also used to identify which zip codes may be promising locations for an offsite facility.

Development and Validation of Binary Logit Model

A binary logit model was developed to identify variables that would predict usage for offsite facilities. The model building procedure involved four tests.

1. Identify significant variables.
2. Check models for goodness of fit.
3. Determine prediction accuracy with a training data set.
4. Determine prediction accuracy with a testing data set.

The tests were performed in sequential order. For example, models that contained insignificant variables (Test 1) were discarded and were not carried forward to Test 2.

Table 28 summarizes the results of the first three tests. The first three models passed Test 1, as they all had significant variables. Only the final model passed Test 2, as Models 1 and 2 did not demonstrate adequate goodness of fit. Test 3 showed that the final model's prediction accuracy was 63%, which was better than the 50% that would have resulted from chance alone.

Results of Test 1: Determine Significance of Independent Variables

The statistical software package SPSS was selected to develop the models and to determine the significance of the independent variables.

The final model shown in the first row of Table 28 suggests that the FDT and perceived variability (VAR) significantly influences a passenger's willingness to use an offsite facility. This model is given in Eq. 16:

Table 28. Binary Logit Models

<table>
<tr><th rowspan="2">Model</th><th rowspan="2">Variables Included[a]</th><th>Test 1[b]</th><th>Test 2[c]</th><th colspan="3">Test 3[d]</th></tr>
<tr><th>Significance</th><th>Hosmer-Lemeshow Goodness-of-Fit</th><th>Use Offsite Facility</th><th>Do Not Use Offsite Facility</th><th>Overall Percentage Accurately Predicted</th></tr>
<tr><td rowspan="2">Final Model</td><td>VAR</td><td>0.000</td><td rowspan="2">0.730</td><td rowspan="2">80.2[e]</td><td rowspan="2">40.0</td><td rowspan="2">63.0</td></tr>
<tr><td>FDT</td><td>0.000</td></tr>
<tr><td rowspan="3">Alternate Model 1</td><td>Ground travel time</td><td>0.000</td><td rowspan="3">0.000</td><td rowspan="3">92.1</td><td rowspan="3">92.6</td><td rowspan="3">92.3</td></tr>
<tr><td>Distance from airport</td><td>0.000</td></tr>
<tr><td>Access mode</td><td>0.000</td></tr>
<tr><td rowspan="3">Alternate Model 2</td><td>$r_{groundtraveltime}$</td><td>0.000</td><td rowspan="3">0.000</td><td rowspan="3">74.7</td><td rowspan="3">92.8</td><td rowspan="3">84.4</td></tr>
<tr><td>$r_{impedance}$</td><td>0.000</td></tr>
<tr><td>$r_{uncertainty}$</td><td>0.000</td></tr>
<tr><td rowspan="3">Alternate Model 3</td><td>VAR</td><td>0.000</td><td rowspan="3">0.091</td><td rowspan="3">90.7</td><td rowspan="3">21.5</td><td rowspan="3">66.3</td></tr>
<tr><td>FDT</td><td>0.000</td></tr>
<tr><td>COST</td><td>0.556</td></tr>
<tr><td rowspan="2">Alternate Model 4</td><td>COST</td><td>0.822</td><td rowspan="2">0.000</td><td rowspan="2">82.9</td><td rowspan="2">32.5</td><td rowspan="2">65.1</td></tr>
<tr><td>VAR</td><td>0.000</td></tr>
<tr><td rowspan="2">Alternate Model 5</td><td>COST</td><td>0.332</td><td rowspan="2">0.000</td><td rowspan="2">100.0</td><td rowspan="2">0.00</td><td rowspan="2">64.8</td></tr>
<tr><td>FDT</td><td>0.000</td></tr>
<tr><td rowspan="3">Alternate Model 6</td><td>FDT</td><td>0.000</td><td rowspan="3">0.966</td><td rowspan="3">100.0</td><td rowspan="3">63.4</td><td rowspan="3">87.1</td></tr>
<tr><td>VAR</td><td>0.048</td></tr>
<tr><td>CITY</td><td>1.000</td></tr>
<tr><td rowspan="2">Alternate Model 7</td><td>FDT</td><td>0.000</td><td rowspan="2">1.000</td><td rowspan="2">100.0</td><td rowspan="2">63.4</td><td rowspan="2">87.1</td></tr>
<tr><td>CITY</td><td>1.000</td></tr>
<tr><td rowspan="2">Alternate Model 8</td><td>VAR</td><td>0.072</td><td rowspan="2">1.000</td><td rowspan="2">100.0</td><td rowspan="2">63.4</td><td rowspan="2">87.1</td></tr>
<tr><td>CITY</td><td>1.000</td></tr>
<tr><td rowspan="4">Alternate Model 9</td><td>FDT</td><td>0.000</td><td rowspan="4">0.960</td><td rowspan="4">100.0</td><td rowspan="4">63.7</td><td rowspan="4">87.2</td></tr>
<tr><td>VAR</td><td>0.048</td></tr>
<tr><td>COST</td><td>0.131</td></tr>
<tr><td>CITY</td><td>1.000</td></tr>
</table>

[a]COST = out-of-pocket dollars spent to access airport such as parking, fuel, tolls, transit or taxi fares; VAR = variability of passenger's travel time to access airport (5, 15, 30, 45 min, or higher); FDT = flight departure time (8 A.M.-10:30 A.M., 10:30 A.M.-1:00 P.M., 1:00 P.M.-3:30 P.M., 3:30 P.M.-6:00 P.M., or later); $r_{groundtraveltime}$ = resistance of ground travel time of individual passengers while accessing airport as determined by airport access quality model; $r_{impedance}$ = resistance of impedance of individual passengers while accessing airport as determined by airport access quality model; $r_{uncertainty}$ = resistance of uncertainty of individual passengers while accessing airport as determined by airport access quality model.

[b]Test 1: determines significance of predictor variables; $p < 0.05$ is desired.

[c]Test 2: determines goodness of fit using H-L test; $p > 0.05$ is desired.

[d]Test 3: determines percentage prediction accuracy using classification tables where all probabilities less than 0.5 are classified as non-users of offsite airport facility and those greater than 0.5 are classified as users of an offsite airport facility

[e]*Example:* 809 respondents used offsite facility to access airport. Model predicted that 649 used terminal; thus percentage accurately predicted was (649/809)*100 = 80.2%.

$$\ln\left(\frac{P_{offsite}}{1 - P_{offsite}}\right) = -1.127*VAR(1) - 0.14*VAR(2) - 0.015*VAR(3) + 0.029*VAR(4)$$
$$- 0.113*VAR(5) - 0.774*FDT(1) - 0.512*FDT(2) - 0.945*FDT(3) - 1.22*FDT(4)$$
$$- 1.467*FDT(5) + 1.534 \qquad \text{(Eq. 16)}$$

where

$P_{offsite}$ = probability of a passenger using an offsite facility

FDT was based on Question 1 (Appendices A and B) as follows: FDT(1): FDT is before 8 A.M.; FDT(2) is 8:00-10:30 A.M.; FDT(3) is 10:30 A.M.-1:00 P.M.; FDT(4) is 1-3:30 P.M.; FDT(5) is 3:30-6:00 P.M.

Variability (VAR) was based on Question 6 (Appendix A) and Question 7 (Appendix B) as follows: VAR(1): ground travel time has less than 5 min of perceived variability; VAR(2): 15 min; VAR(3): 30 min; VAR(4): 45 min; VAR(5): 1 hr or more of perceived variability

Table 29 shows the significance and the 95% confidence intervals for the variables in Eq. 16.

Table 29. Binary Logit Model Output

Variables Used in Model	B	Significance	Exp(B)	95% Confidence Interval for Exp(B) Lower	Upper
VAR[a]		.000			
VAR(1)	-1.127	.000	.324	.230	.455
VAR(2)	-.140	.373	.869	.639	1.183
VAR(3)	-.015	.944	.985	.655	1.482
VAR(4)	.029	.928	1.030	.546	1.942
VAR(5)	-.113	.778	.893	.407	1.958
FDT[b]		.000			
FDT(1)	-.774	.006	.461	.264	.805
FDT(2)	-.512	.041	.599	.367	.979
FDT(3)	-.945	.000	.389	.242	.624
FDT(4)	-1.220	.000	.295	.181	.482
FDT(5)	-1.467	.000	.231	.141	.378
Constant	1.534	.000	4.637		

[a]Perceived variability in ground travel time coded as follows. VAR(1): less than 5 min; VAR(2): 15 min; VAR(3): 30 min; VAR(4): 45 min; VAR(5): 1 hour or more of perceived variability.
[b]Scheduled flight departure time coded as follows: FDT(1): prior to 8 A.M.; FDT(2): 8:00-10:30 A.M.; FDT(3): 10:30 A.M.-1:00 P.M.; FDT(4): 1:00-3:30 P.M.; FDT(5): 3:30-6:00 P.M.

Results of Test 2: Goodness of Fit

A goodness-of-fit test was conducted to determine whether there was a statistically significant difference between the observed values and the values predicted by the model. The Hosmer and Lemeshow (H-L) test was used (Hosmer and Lemeshow, 2000). If the H-L test statistic is greater than 0.05, the null hypothesis that there is no difference between observed and predicted values is not rejected and, by extension, the model is appropriate for the data set. Table 30 indicates that there was no difference between observed and predicted values.

Appendix D discusses how other tests of significance may be used instead of the H-L test.

Table 30. Hosmer and Lemeshow Test

Chi-square	Degrees of Freedom	Significance
5.253	8	0.73

Results of Test 3: Prediction Accuracy with Training Data

Table 31 shows that the model predicted the correct response for 63% of the cases. There were 605 (= 242 + 363) respondents who indicated they would not use an offsite facility and 809 (= 160 + 649) respondents who indicated they would use an offsite facility. Application of Eq. 16 showed that of the 605 respondents not willing to use an offsite facility, 242 were correctly predicted as not using such a facility whereas 363 were incorrectly predicted as using it. Similarly, of the 809 respondents that were using an offsite facility, 649 responses were correctly predicted as using it and 160 were incorrectly predicted as not using it.

Table 31. Prediction Accuracy with Training Data

Observed		Predicted		
		Y		% Error
		Will not use offsite facility	Will use offsite facility	
Y	Will not use offsite facility	242	363	60%
	Will use offsite facility	160	649	20%
Overall % error				37%

Eq. 16 predicts the odds of a passenger using an offsite airport facility, given his or her flight departure time and perceived variability in ground travel time. For example, one may assume a passenger with these characteristics:

1. A 30-min variability is perceived in ground travel time (hence, VAR = 3).
2. The flight is scheduled to depart at 10:00 A.M. (hence, FDT = 2).

Accordingly, Eq. 16 may be computed as:

$$\log\left(\frac{P_{\text{offsite}}}{1-P_{\text{offsite}}}\right) = -0.015-0.512+1.534$$

The odds prediction equation is

$$\text{ODDS} = \frac{P_{\text{offsite}}}{1-P_{\text{offsite}}} = \exp\,(-0.015 - 0.512 + 1.534) = 2.737$$

Thus, passengers with these characteristics are 2.737 times more likely to use an offsite airport facility than not to use it.

The odds can be easily converted into a probability. For this group of passengers,

$$P_{\text{offsite}} = \frac{\text{ODDS}}{1+\text{ODDS}} = \frac{2.737}{1+2.737} = 0.73$$

Thus, this model predicted that 73% of passengers with these characteristics (VAR = 3 and FDT = 2) are willing to use an offsite airport facility. Eq. 16 may be repeated to determine the likelihood of each market segment using an offsite airport facility. For example, Table 32 shows that for passengers whose flight departure time is before 8 A.M. (FDT = 1) and whose perceived variability is less than 5 min (VAR = 1), 41% are likely to use an offsite airport facility. If this probability were applied to a single passenger, because the expected frequency would be less than 0.5, the result suggests that a single passenger whose FDT = 1 and VAR = 1 would not be expected to use the facility.

Table 32 reveals that for a given variability range, the probability of using an offsite airport facility increases up to FDT = 2, after which it decreases. For a given flight departure time range, the probability of using an offsite airport facility increases up to VAR = 4, after which it decreases. Thus, passengers with VAR = 4 and FDT = 2 have the highest probability of using an offsite airport facility, and passengers with VAR = 1 and FDT = 5 have the lowest such probability. Using the 95% confidence interval values shown in Table 29, confidence intervals for the probabilities shown in Table 32 were developed. Figure 6 depicts the confidence interval for the market segment FDT = 2 and VAR = 4 and the interval for the market segment FDT = 5 and VAR = 1. There is no overlap between the two market segments, suggesting that there is a significant difference between them.

As shown in Appendix E, when there are more than a couple thousand passengers evenly distributed among the cells, the differences in Table 32 are statistically significant.

Table 32. Probability of Using Offsite Airport Facilities

Variability (VAR)	**Flight Departure Time (FDT)**				
	1 (before 8 A.M.)	**2 (8-10:30 a.m.)**	**3 (10:30 a.m.-1 P.M.)**	**4 (1-3:30 P.M.)**	**5 (3:30-6 P.M.)**
1 (5 min)	41%	47%	37%	31%	26%
2 (15 min)	65%	71%	61%	54%	48%
3 (30 min)	68%	73%	64%	57%	51%
4 (45 min)	69%	74%	65%	58%	52%
5 (1 hr or more)	66%	71%	62%	55%	49%

Results of Test 4: Prediction Accuracy with Testing Data

The final model that was chosen in Table 28 and analyzed in Table 32 was based only on 90% of the data collected for this study. The remaining 10% of the data, which were not used to calibrate the model, comprised the "test" data set. Table 33 shows the percentage error obtained with these data. Although there is only a 13% error in accurately predicting the usage of an

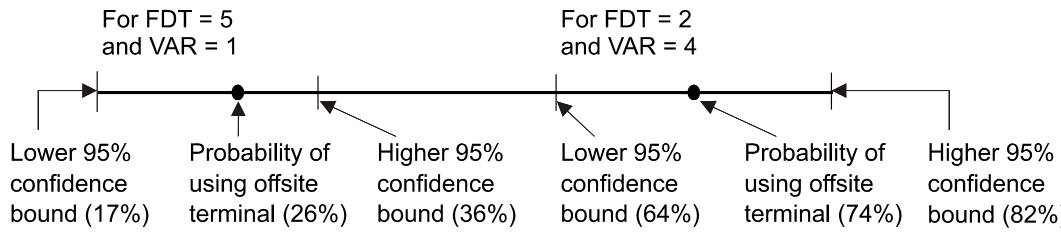

Figure 6. Confidence Interval for Market Segments

offsite airport facility, there is a 73% error in accurately predicting the non-usage of an offsite airport facility. The overall percentage error in prediction is 42%. As would be expected, the overall percentage error with the testing data set is larger (42% as shown in Table 33) than the overall percentage error with the training data set (37% as shown in Table 31).

Table 33. Prediction Accuracy with Testing Data[a]

	Predicted		
Observed	**Will not use offsite airport facility**	**Will use offsite airport facility**	**Percentage error**
Will not use offsite airport facility	20	54	73%
Will use offsite airport facility	10	67	13%
Overall percentage error			42%

[a]The test data from Table 33 showed that 20 + 54 = 74 respondents will not use the offsite facility, whereas 10 + 67 = 77 respondents indicated they will use the offsite facility. The implication that 77 / (77 + 74) = 51% of respondents might use the facility was used in estimating the upper limit of potential emissions reductions for an offsite facility located in Richmond as discussed in Volume I of this study (Goswami et al., 2008).

Development and Validation of a Cross-Classification Model

As an alternative to the binary logit model, a cross-classification model was developed using the same two independent variables discussed previously: FDT and perceived variability in ground travel time (VAR). Table 34 shows the percentage of passengers willing to use an offsite airport facility for each FDT and VAR combination.

As with the binary logit model, the data had been split into two sets: a training set used for calibration and a separate testing data set. With the testing data, the cross-classification model had an absolute percentage error of 52% when predicting the usage of offsite airport

Table 34. Percentage of Passengers Using Offsite Airport Facilities in Specific Market Segments

	Flight Departure Time (FDT)				
Variability (VAR)	**1 (before 8 A.M.)**	**2 (8-10:30 a.m.)**	**3 (10:30 a.m.-1 P.M.)**	**4 (1- 3:30 P.M.)**	**5 (3:30 -6 P.M.)**
1 (5 min)	34%	39%	43%	32%	27%
2 (15 min)	62%	71%	57%	56%	55%
3 (30 min)	77%	79%	52%	68%	58%
4 (45 min)	75%	92%	56%	50%	50%
5 (1 hr or more)	100%	33%	63%	67%	17%

facilities and an absolute percentage error of 29% when predicting the non-usage of offsite airport facilities (see Table 35). The overall estimated absolute percentage error is 41%, which is comparable to the 42% overall absolute percentage error with the logit model.

Table 35. Comparison of Absolute Percentage Errors Between Models

Passenger Choice	Binary Logit Model	Cross-classification Model
Will use offsite airport facility	13%	52%
Will not use offsite airport facility	73%	29%
Overall	42%	41%[a]

[a]Absolute percentage error of 41% was calculated by computing total number of incorrect predictions divided by total number of correct predictions.

Model Application: Selection of Promising Zip Codes for Offsite Facility

Tables 32 and 34 show that the logit model and the cross-classification model have similar predictions in each market segment in terms of the percentage of passengers who are willing to use an offsite facility. Table 36 shows the difference in predicted percentages between the two models (shown in Tables 32 and Table 34) and their sample sizes. In most cases, the differences are less than 10%, and discrepant results tend to occur for those market segments the sample size is quite small. For example, the FDT 1 and VAR 5 market segment shows the highest discrepancy in the predicted percentage (34%) and the lowest sample size (*n* = 1).

To determine the most promising zip codes for locating an offsite facility, a threshold probability of 60% may be established. According to Tables 32 and 34, the market segments that have a 60% or higher probability of using an offsite airport facility are as follows: FDT 1, VAR 2 through VAR 5; FDT 2, VAR 2 through VAR 4; and FDT 3, VAR 5. Table 37 shows the originating zip codes of the air passengers departing from BOS and SFO (the airports that have the partial offsite airport facilities) and their corresponding market segments.

Table 36. Difference in Prediction Percentage of Tables 32 and 34

Variability (VAR)	Flight Departure Time (FDT)									
	1 (before 8 A.M.)		2 (8-10:30 A.M.		3 (10:30 A.M. -1 P.M.)		4 (1-3:30 P.M.)		5 (3:30-6 P.M.)	
	n[a]	Difference	n	Difference	n	Difference	n	Difference	n	Difference
1 (5 min)	29	7%[b]	56	8%	101	6%	50	1%	45	1%
2 (15 min)	53	3%	106	0%	127	4%	94	2%	76	7%
3 (30 min)	13	9%	34	6%	31	12%	28	11%	26	7%
4 (45 min)	4	6%	12	18%	9	9%	4	8%	8	2%
5 (1 hr or more)	1	34%	3	38%	8	1%	6	12%	6	32%

[a]Sample size.
[b]Absolute difference between cross-classification and logit model predictions; e.g., difference of 7% is obtained by subtracting 34% prediction in corresponding cell in Table 34 (FDT 1 and VAR 1) from 41% prediction in corresponding cell in Table 32.

Table 37. Zip Codes with Offsite Airport Facility Usage

Airport	FDT 1[a]					FDT 2[a]						FDT 3[a]
	VAR 2[b]		VAR 3[b]	VAR 4[b]	VAR 5[b]	VAR 2[b]			VAR 3[b]		VAR 4[b]	VAR 5[b]
BOS	01701(3[c])	02026	02341	02134	-	01701(4)	02421	02338	01701	02767	02188	02770(2)
	01760(2)	01887	02368	02126		02043(3)	01876	01949	02351	02770	02045	01069
	01588(2)	02343	01852	03053		01867(3)	01810	02062	02339	02375	03053	
	01778(2)	01450	01776	01721		01776(3)	01830	02081	02767	01460	01803	
	02072	01741	01534			01801(2)	03087	02050	01867	02180	02315	
	02045	01772	02053			02368(2)	03076	02302	01867	01453	02103	
	02301	01746	01702			01886(2)	02180	02842	02050	01702	01752	
	02481	01590				01746(2)	02301	02332	02050	01002		
	01754					01772(2)	02066	01748	01821	02332		
						02351	01760	01519	01778	01749		
						02188	02493	01742				
						01803	01721	01702				
SFO	94904(3)	94945	94946	94925	94949	94960(3)	94965(2)	94931	94903	94965	94930	-
	94901(3)	95476				94939(3)	94903(2)	94965	94948	95451	95476	
	94946	94925				94941(3)	94701	94947	94941	94901		
	94925	94939				94904(3)	91917	94903				
	94930	94973				94901(3)	92270	93105				
	94925	94937				94949(2)	95476					
	94941	94903				94957(2)						

BOS = Boston Logan International Airport, SFO = San Francisco International Airport.

[a]Scheduled flight departure time: FDT(1): before 8 A.M.; FDT(2): 8-10:30 A.M.; FDT(3): 10:30 A.M.-1 P.M.

[b]Perceived variability in ground travel time: VAR(2): 15 min; VAR(3): 30 min; VAR(4): 45 min; VAR(5): 1 hr or more.

[c]*Example*: There were 3 passengers whose flight departure time was prior to 8 A.M. and who perceived variability in ground travel time to airport to be 15 min.

Table 37 shows that the model predicts the zip codes 01701 for BOS and 94901 for SFO as the ones to have passengers with a high probability of using an offsite airport facility. In addition, as shown previously in Table 11, the same zip codes, i.e., 01701 and 94901 for BOS and SFO, respectively, are among the top three that generate a high percentage of air passengers. In addition, the Framingham offsite airport facility of the Logan Express service is located in the zip code 01701 and the San Rafael offsite airport facility of the Marin Airporter service is located in the zip code 94901. Thus, the following are true for zip codes 01701 and 94901:

- According to the survey results, they generate a high percentage of air passengers.
- They are predicted by the offsite facility demand model to be zip codes likely to generate passengers that would use an offsite airport facility.
- They are the locations of an existing offsite airport facility.

Based on the approach used for constructing Table 37, Table 38 shows the promising zip codes for RIC and BWI, which are two airports that are candidates for a future offsite airport facility because of their low airport access quality.

Table 38 shows that in the case of RIC, two zip codes, 23220 and 23112, fall in the market segment that has been predicted to have probable users of an offsite airport facility. Returning to Table 11, these zip codes are two of the top three air passenger-generating zip codes. Thus, based on the example of the zip code 01701 (having an offsite airport facility for BOS), the model suggests that zip codes 23220 (Richmond, Virginia) and 23112 (Midlothian, Virginia) could be considered as possible locations for offsite airport facilities when only demand characteristics are considered.

Table 38. Market Segments and Originating Zip Codes

	FDT 1[a]				FDT 2[a]			FDT 3[a]
Airport	**VAR 2[b]**	**VAR 3[b]**	**VAR 4[b]**	**VAR 5[b]**	**VAR 2[b]**	**VAR 3[b]**	**VAR 4[b]**	**VAR 5[b]**
RIC	23832	-	-	-	23238 (2[c])	23236	-	
	23803	-	-	-	23220 (2)	23002	-	
		-	-	-	23112		-	
		-	-	-	23060		-	
		-	-	-	23059		-	
		-	-	-	23237		-	
		-	-	-	23225		-	
		-	-	-	23233		-	
		-	-	-	23235		-	
BWI		-	-	-	21218	21042	-	23708
		-	-	-	28215		-	22153
		-	-	-	20878		-	20744
		-	-	-	21093		-	21801

RIC = Richmond International Airport, BWI = Baltimore/Washington International Thurgood Marshall Airport.

[a]Scheduled flight departure time: FDT(1): before 8 A.M.; FDT(2): 8-10:30 A.M.; FDT(3): 10:30 A.M.-1 P.M.

[b]Perceived variability in ground travel time: VAR(2): 15 min; VAR(3): 30 min; VAR(4): 45 min; VAR(5): 1 hr or more.

[c]There were 2 passengers whose flight departure time was between 8-10:30 A.M. and who perceived variability in ground travel time to airport to be 15 min.

DISCUSSION:
APPLYING THE SEQUENTIAL MODELS TO OTHER LOCATIONS

Tasks 3 and 4 described the development of two classes of models to determine the demand of offsite facilities: airport access quality models and offsite facility usage models. This study demonstrated how to apply these models in a sequential fashion and how these models may be considered at other locations. Planners who desire to use this approach to investigate passenger demand for an offsite facility should first use the airport access quality model to determine the current total resistance to airport access and then apply the offsite facility usage model to calculate the probability of passengers who would be willing to use an offsite facility.

For example, one may consider just two airports: CHO and RIC. The airport access quality models in this study suggest that CHO currently has the lowest total resistance to airport access and hence would be the least likely candidate for an offsite facility. By contrast, the airport access quality models in this report suggest that RIC has higher resistance and thus is a more likely candidate for an offsite facility. The offsite facility usage model may then be used at RIC to determine the probability that certain market segments of passengers would be willing to use a facility. This model showed that those passengers with high ground travel time variability and flight departure times between 8 and 10:30 A.M. are promising candidates.

The scope of this methodology is limited to demand estimation. Thus, a next step with a promising airport such as RIC is to determine economic and technical feasibility. Thus, factors such as impact on airport parking revenue and the provision of transportation services would need to be considered as part of a site-specific study at a given airport such as RIC.

CONCLUSIONS

- *Total destination airport travel time was much higher than average flight time.* The 1,700 surveys at six airports revealed that average flight time was only 52% of the total destination airport travel time. The average flight time varied from 2 hr 32 min to 5 hr 55 min, whereas the average destination airport travel time varied from 4 hr 44 min to 9 hr 2 min.

- *Non-airport activity time is the largest proportion of pre-flight time.* The 652 surveys obtained from four airports where passengers accessed the airport directly suggest that of the 2 hr 31 min average pre-flight time, passengers have an average non-airport activity time of 1 hr 47 min. The average total processing time for passengers to check in was slightly greater than 7 min, of which they spent an average of slightly less than 4 min waiting in the queue and a comparable amount of time at the check-in counter. The passengers also spent an average of 4 min at the security clearance queue, and their average ground travel time to the airport was 38 min.

- *Processing times at check-in counters show high variability but small values.* A total of 1,432 observations at the check-in counters of four airports showed that the average processing time was 7 min 25 sec, with a range of 4 min at CHO and 12 min 31 sec at ORF.

Despite its small magnitude, this processing time shows high variability. The coefficient of variation of the processing time varied from 71% at BWI to 104% at ORF.

- *Airport access quality models suggest RIC and BWI have a higher resistance of airport access as compared to CHO and ORF.* Models were developed to determine the difficulty of access trip to the airport, where resistance of airport access is based on access cost, processing time at check-in counters, number of impedances encountered by passengers, ground travel time, and perceived variability of ground travel time. The models suggested that total resistance of access at CHO (a small airport in a less urban area) was lowest, whereas the total resistance of access for BWI and RIC (larger airports in more urban areas) was higher. Because of their high resistance of airport access, RIC and BWI are likely more suitable for an offsite airport facility.

- *Survey data suggest there may be some demand for offsite facilities.* The survey data indicated that 68% of passengers who traveled directly to the airport were willing to use an offsite airport facility if it were available and if it improved the access trip in some way. Of the passengers who currently used an offsite facility, 70% expressed interest in expanded services such as baggage and passenger check in.

- *Passengers with a scheduled flight departure time between 8:00 and 10:30 A.M. and a perceived variability in ground travel time (VAR) of 45 min appear likely to use offsite facilities.* The offsite facility usage model predicted that passengers whose FDT was between 8:00 A.M. and 10:30 A.M. and whose perceived variability in ground travel time was 45 min had the highest probability of using an offsite airport facility (74%). By contrast, the same model predicted that the passengers having an FDT between 3:30 P.M. and 6:00 P.M. and a perceived variability in ground travel time of 5 min had the lowest probability of using an offsite airport facility (26%).

- *The cross-classification technique has promise for the airport access quality models and the offsite facility usage models.* For the airport access quality models, the linear regression method gave unreliable results; only the cross-classification approach was useful. For the offsite facility usage models, the binary logit and cross-classification approaches were both useful and had a similar prediction accuracy (42% error for the binary logit approach and 41% error for the cross classification approach).

RECOMMENDATIONS

No single entity is charged with implementing these recommendations as airport offsite passenger service facilities affect two separate transportation modes. Recommendations 1 and 2 apply to members of the research community who can support the development of such facilities. Recommendations 3 and 4 apply to state or local planners who are interested in intermodal transportation facilities.

1. *The airport access quality model should be used to develop a total resistance for the access to airports based on parameters such as impedance, access cost, ground travel time, processing time, and variability*. An offsite airport facility should be further considered if an airport's resistance is high.

2. *The cross-classification technique, rather than the linear regression technique, should be used to determine the resistance of access trip at airports.* Both techniques were tested within the context of the airport access quality model, but only the cross-classification technique gave reliable results.

3. *If an offsite airport facility is considered, it should be targeted at specific market segments*. For example, the results of the binary logit offsite airport facility usage model developed in this study suggests that offsite airport facilities are more likely to be used by passengers who meet two criteria. These are (1) air passengers with a high perceived variability in ground travel time and (2) a scheduled flight departure time during the morning rush hour.

4. *If an offsite airport facility is to be considered at a given airport, demand characteristics should be one criterion that is used to identify promising locations in a given metropolitan area.* For example, this study found that zip codes 23220 and 23112 are candidate locations for offsite airport facilities that would serve RIC. The reason is that according to the airport access model, RIC has a lowest resistance score (relative to more rural airports in Virginia), and according to the offsite airport facility usage model, passengers having the zip codes 23220 and 23112 as their origin have a higher probability of using an offsite airport facility than passengers without those characteristics.

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APPENDIX A

QUESTIONNAIRE DISTRIBUTED AT AIRPORTS WITHOUT OFFSITE FACILITIES*

1. What is your flight's scheduled departure time__________________ AM/PM and scheduled arrival time (at **final** destination) __________________ AM/PM

2. What time did you reach the airport terminal today? __________________ AM/PM

3. How long did it take you to travel (from home, work, hotel, etc.) to get to the airport terminal? ____(minutes)

4. Please provide the *location* of your origin (home, work, hotel, etc.)
__________________________________street address **OR** ______zip code and ___________neighborhood

5. How did you get to the airport today? (include all applicable)
__Drove personal automobile and parked
__Received a ride to the airport (from family, colleague, etc)
__Drove a rental vehicle and parked
_Other ______________________ (specify)
__Hired a taxicab
__Took a bus
__Took light rail

6. How does the time to reach the terminal vary each time you access the airport?
__Varies by less than 5 minutes __Varies by 15 minutes __Varies by 30 minutes
__Varies by 45 minutes __Varies by more than 1 hour __Unknown

7. What is the cost of your flight ticket? $________________

8. What was your total cost of travel (from home, work, hotel, etc.) to the terminal? (include all applicable)
$______Parking $_______Mileage $______Transit fare
$______Taxi fare $_______Other ____________________ (specify)

9. So far today, how satisfied are you with your trip to the airport?
_____Very satisfied, and do not want improvements _______Satisfied, but expect improvements
_____Not satisfied, and want improvements

10. Would you be willing to check-in at an **offsite airport facility*** if it was to improve your access to the airport?
__Yes __No

If yes, **RANK** the benefits below, "1" being the most important:
__Shorter travel time to the airport terminal
__ Lower costs to get to the airport terminal
__Shorter waiting time at check-in queue
__Quicker processing times at check-in counters
__Certainty in access times to the airport
__Other ________________________ (specify)

Thank you very much for your participation!
For comments, suggestions, or questions contact Arkopal Goswami, Virginia Transportation Research Council, 530 Edgemont Road, Charlottesville, VA. 22903 Phone: (434) 293-1907 Fax: (434) 293-1990

*Questionnaire was distributed to passengers inside the terminal at CHO, RIC, ORF, and BWI.

APPENDIX B

QUESTIONNAIRE DISTRIBUTED AT AIRPORTS WITH OFFSITE FACILITIES*

---

1. Today's scheduled flight departure time ______ AM/PM
2. Scheduled flight arrival time at destination ______ AM/PM
3. Today's time you reached Marin Airporter terminal ______ AM/PM
4. How did you reach Marin Airporter terminal today? (check all that apply)
   __Drove personal auto and parked __Hired a taxi
   __Received a ride __Took a bus __Other______________

5. What is the zip code of your origin (home, work, hotel, etc.)? ____________
6. How long (minutes) did it take you to get to SFO today?
   ______from origin to Marin Airporter terminal ____wait at Marin Airporter terminal
   ______from Marin Airporter terminal to SFO

7. How does the total time taken to reach SFO vary each time you access the airport?
   __Varies by less than 5 minutes __Varies by 15 minutes __Varies by 30 minutes
   __Varies by 45 minutes __Varies by more than 1 hour __Unknown

8. What is the round-trip cost of your flight ticket? $___________
9. What is your total cost of travel to get to SFO today? $_________
   (Include all costs: Marin Airporter fare, parking costs, tolls, etc.)

10. How many pieces of baggage will you be checking-in today? ______

11. Why did you prefer to take the Marin Airporter rather than going directly to the airport?
    __Shorter travel time to the airport terminal __ Lower costs to get to the airport terminal
    __Certainty in access times to the airport terminal __Convenient parking compared to airport

12. When did you first use the Marin Airporter service?
    __Today __Used earlier ____________ (specify which year)

13. How was your overall experience with the Marin Airporter today?
    __Very poor __Poor __Good __Very good __Excellent

14. Would future additional services* at Marin Airporter terminal help improve your access to SFO?
    __Yes __No
    *(In addition to the services already offered, you could receive your boarding pass, and/or be able to check your baggage through to your destination airport).

If yes, rank the benefits of such an offsite airport facility, with "1" being the most important:
__Shorter waiting time at check-in queue __Quicker processing times at check-in counters
__Less variability in access times to the airport __Convenience of checking-in baggage
__Other ______________________________

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*Questionnaire was distributed to passengers using buses providing access to SFO from offsite facilities. (A similar questionnaire was distributed on board buses providing access to BOS from offsite facilities.)

APPENDIX C

CROSS-CLASSIFICATION AIRPORT ACCESS QUALITY MODEL RESULTS

Airport	Predicted Resistance Variables (y_i)			Resistance Values (r_i)	Total Resistance (R_{total})
CHO		Max	3.00		0.29
	Impedance	Min	1.00	0.24	
		Average	1.48		
		Max	$31.98		
	Access cost	Min	$3.26	0.46	
		Average	$16.51		
		Max	85.000		
	Ground travel time	Min	14.583	0.19	
		Average	27.931		
		Max	0.233		
	Processing time	Min	0.042	0.26	
		Average	0.091		
		Max	11.00		
	Uncertainty	Min	3.00	0.35	
		Average	5.98		
RIC		Max	3.00		0.38
	Impedance	Min	1.00	0.24	
		Average	1.48		
		Max	$31.98		
	Access cost	Min	$3.26	0.49	
		Average	$17.35		
		Max	85.00		
	Ground travel time	Min	14.58	0.36	
		Average	40.04		
		Max	0.233		
	Processing time	Min	0.042	0.37	
		Average	0.114		
		Max	11.00		
	Uncertainty	Min	3.00	0.52	
		Average	7.19		
ORF		Max	3.00		0.36
	Impedance	Min	1.00	0.24	
		Average	1.48		
		Max	$31.98		
	Access cost	Min	$3.26	0.56	
		Average	$19.29		
		Max	85.00		
	Ground travel time	Min	14.58	0.28	
		Average	34.62		
		Max	0.233		
	Processing time	Min	0.042	0.37	
		Average	0.112		
		Max	11.00		
	Uncertainty	Min	3.00	0.46	
		Average	6.68		

Airport	Predicted Resistance Variables (y_i)			Resistance Values (r_i)	Total Resistance (R_{total})
BWI		Max	3.00		0.42
	Impedance	Min	1.00	0.27	
		Average	1.54		
		Max	$31.98		
	Access cost	Min	$3.26	0.59	
		Average	$20.14		
		Max	85.00		
	Ground travel time	Min	14.58	0.42	
		Average	44.17		
		Max	0.233		
	Processing time	Min	0.042	0.35	
		Average	0.109		
		Max	11.00		
	Uncertainty	Min	3.00	0.53	
		Average	7.23		

APPENDIX D

RATIONALE FOR USING THE HOSMER AND LEMESHOW TEST

Table 28 showed the final model chosen for this study and nine alternative models that were considered but not chosen. For each model, Table 28 gives the corresponding goodness-of-fit results and the prediction accuracy. The Hosmer and Lemeshow (H-L) test is the default goodness-of-fit measure provided in the SPSS software package and was used in this report. However, SPSS also develops 2X2 classification tables that help determine the percentage accuracy of predictions and that can be used to develop an alternative goodness-of-fit measure. These two goodness-of-fit measures, i.e., the one based on the H-L test and the other based on the 2x2 chi-square test—may give contradictory results.

This contradiction occurred when Models 1 and 2 in Table 28 were considered. They failed the H-L test (and hence were not selected as the final model, despite their high percentage accuracy of prediction). However, a 2x2 chi-square test showed that there is no significant difference between the observed and predicted values. This appendix shows the calculations necessary to perform the H-L test and the 2x2 chi-square test and why the former was used to select the most appropriate model in Tables 28 and 32.

Model 1 was developed using three variables: ground travel time, distance from airport, and access mode. As reflected in Table D1, *access mode* is a binary vector, where each record has a value of "1" for either the AccessMode(1) index or the AccessMode(2) index and a value of "0" for the other index.

The H-L test revealed that there was a significant difference between observed and predicted values (see Table D2).

The H-L test is performed by dividing the predicted probabilities into deciles and then computing a Pearson chi-square statistic that compares the predicted frequencies to the observed

Table D1. Variables in Model 1

Variables		B	Significance	Exp(B)	95.0% Confidence Interval for EXP(B) Lower	Upper
	Ground Travel Time	-.109	.000	.897	.870	.924
	DistancefromAirport	.160	.000	1.173	1.148	1.200
	AccessMode		.000			
	AccessMode(1)	-.106	.771	.900	.441	1.833
	AccessMode(2)	1.594	.000	4.922	2.381	10.173
	Constant	-5.780	.000	.003		

Table D-2. Hosmer and Lemeshow Test for Model 1

Chi-square	Degrees of Freedom	Significance
190.100	8	.000

frequencies, shown in Table D3. The 10 ordered categories are created based on their estimated probability; those with estimated probability below 0.1 form one category, those with estimated probability between 0.1 and 0.2 form a second category, and so on such that those with probability 0.9 to 1.0 form the tenth category. Each of these categories is further divided into two groups based on the actual observed outcome variable, which in this case is success or failure. The expected frequencies for each of the cells are obtained from the model.

The H-L goodness-of-fit statistic is then calculated from the frequencies in Table D3 using Eq. D-1.

$$\hat{C} = \sum_{j=1}^{10} \frac{\left(E_j - O_j\right)^2}{E_j\left(1 - \frac{E_j}{n_j}\right)} \sim \chi_8^2 \qquad \text{(Eq. D1)}$$

where

n_j = Number of observations in the j^{th} group
$O_j = \sum_i y_{ij}$ = observed number of cases in the j^{th} group
$E_j = \sum_i \hat{p}_{ij}$ = expected number of cases in the j^{th} group.

A comparison of observed and expected frequencies within each decile in Table D3 shows that observed and expected frequencies are similar in most cases with one exception: the tenth decile. That discrepancy is reflected in the high C value, shown in Table D3 as 174.52. The reader should note that the sum of all the C-values in Table D3 is 189.7, which is similar to the value of 190.1 as shown in Table D-2.

Table D3. Contingency Table for Hosmer-Lemeshow Test

		Y = 0		**Y = 1**		**Total**	**Hosmer-Lemeshow Statistic**
		Observed	**Expected**	**Observed**	**Expected**	**n_j**	**C**
Deciles	1	81	80.447	0	.553	81	0.56
	2	81	79.401	0	1.599	81	1.63
	3	79	76.907	2	4.093	81	1.28
	4	75	71.554	6	9.446	81	1.42
	5	57	55.788	24	25.212	81	0.08
	6	12	24.699	69	56.301	81	9.39
	7	8	9.383	73	71.617	81	0.23
	8	4	3.766	77	77.234	81	0.02
	9	2	.967	79	80.033	81	1.12
	10	4	.088	77	80.912	81	174.52

The alternate 2x2 chi-square test for goodness of fit is conducted using the classification table (Table D4) developed for the model. The model also shows a high percentage prediction accuracy of 92.3%.

This high *p*-value, shown in Table D-5, suggests that there is no significant difference between the observed and the expected values, thus suggesting a good fit. Further, a 2x2 chi-square test (Table D6) performed on the selected model (based on Table 31) shows that there is a significant difference between observed and expected values, despite passing the H-L test (Table 30).

Thus the selection of Alternative Model 1 is supported on the basis of the 2x2 chi-square goodness of fit (Table D5) along with the high percentage prediction accuracy (Table D4), whereas the selection of the Final Model is supported by the H-L test (Table 30) along with 63.0% percentage prediction accuracy (Table 31). Thus, one might ask why the selected model was chosen since it failed the 2x2 chi-square test and had a lower percentage prediction error than Alternative Model 1.

The H-L test was chosen instead of the 2x2 chi-square test because the former measures the robustness of the model by predicting precise numeric probabilities of offsite facility usage.

Table D4. Logit Classification for Model 1

Observed		**Predicted**		
		Y		**Percentage Correct**
		Will not use offsite facility	Will use offsite facility	
Y	Will not use offsite facility	373	30	92.6
	Will use offsite facility	32	375	92.1
Overall Percentage				92.3

Table D-5. 2X2 Chi-square Test for Model 1

Passenger Choice	**Actual Values**		**Expected Values**		
	Predicted	**Actual**	**Predicted**	**Actual**	
Will not use offsite facility	403	405	404	404	
Will use offsite facility	407	405	406	406	
				Chi-square test *p*-value =	0.921

Table D6. 2x2 Chi-square Test for Final Selected Model

Passenger Choice	**Actual Values**		**Expected Values**		
	Predicted	**Actual**	**Predicted**	**Actual**	
Will not use offsite facility	605	402	504	504	
Will use offsite facility	809	1012	911	911	
				Chi-square test *p*-value =	0.000

That is, the 2x2 chi-square test determines only whether a passenger would use an offsite airport facility or not, reflected as a cut-off value chosen as 0.5. Thus, if the estimated probability is greater than 0.5, the 2x2 chi-square test presumes the expected value is 1 (i.e., the passenger will use an offsite airport facility). Similarly, if the probability is less than 0.5, the test sets the expected value to 0 (i.e., the passenger will not use an offsite airport facility). Thus, although there may be little difference between a probability of 0.48 and 0.52, the use of an 0.5 value as a boundary would classify these two individuals as completely different.

As an illustration, Table D7 shows four boundary values: 0.5, 0.52, 0.55, and 0.60. Changing these boundary values could yield different chi-square test results. In fact, a boundary value of 0.55 shows no significant difference between observed and predicted values.

Thus, the *p*-value derived from such classification tables is sensitive to the assumption that 0.50 represents an appropriate boundary condition for willingness to use an offsite facility. Because the H-L test does not appear to be sensitive to this boundary condition, it was chosen as the criterion for selecting models in Table 32.

Table D7. Cutoff value vs. Significance

Cutoff Value	2x2 Chi-square Test *p*-value	H-L Test *p*-value
0.50	< 0.0001	0.73
0.52	< 0.0001	0.73
0.55	0.82	0.73
0.60	< 0.0001	0.73

APPENDIX E

STATISTICALLY SIGNIFICANT DIFFERENCES IN NUMBER OF PASSENGERS WILLING TO USE AN OFFSITE FACILITY

Figure 6 in the body of the report illustrates how to detect statistically significant differences among the *percentage* of passengers willing to use an offsite airport facility. However, Figure 6 alone does not indicate statistically significant differences among the *number* of passengers willing to use an offsite airport facility. Whether there is a statistically significant difference in the number of passengers for different cells in Table 32 depends, in part, on the size of the sample of passengers under consideration. Setting aside statistical considerations, one may consider, for example, the first two percentages shown in Table 32: 41% and 47%. For a sample of five passengers, these two percentages yield the same result: two passengers who use the offsite airport facility. For a sample of 5,000 passengers, these two percentages yield different results of (41%)*(5,000) = 2,050 passengers and (47%)*(5,000) = 2,350 passengers, respectively.

Applying Table 32 to Market of 250 Total Passengers

A chi-square test may be used to detect the sample size for which the percentages in Table 32 yield a statistically significant difference. For example, if the sample size is 10 passengers in each of the 25 market segments (cells) of Table 32, the upper left cell (VAR 1, FDT 1) suggests (41%)(10) = 4.1 passengers who will use the offsite airport facility, whereas the next cell to the right (VAR 1, FDT 2) suggests (47%)(10) = 4.7 passengers using the offsite airport facility, and so forth, with the bottom right cell (VAR 5, FDT 5) suggesting (49%)(10) = 4.9 passengers using the offsite airport facility. Summing all 25 values for each cell yields a total of 141.5 passengers using the offsite airport facility, with an average value of 141.5/25 = 5.66 passengers per cell. Eq. E1 yields a test statistic Q, which indicates the extent to which these 25 individual cell values (4.1, 4.7, 4.9, and so forth) deviate from the average cell value of 5.66.

$$Q = \sum_{\mathrm{VAR}=1}^{5} \sum_{\mathrm{FDT}=1}^{5} \frac{(\text{Observed Cell Value} - \text{Average Cell Value})^2}{\text{Average Cell Value}} \qquad \text{(Eq. E1)}$$

$$Q = \frac{(4.1-5.66)^2}{5.66} + \frac{(4.7-5.66)^2}{5.66} + \ldots + \frac{(4.9-5.66)^2}{5.66} = 4.1$$

The variable Q in Eq. E1 has a chi-square distribution with 24 degrees of freedom such that the 95th percentile of this distribution is 36.4. This fact serves as the basis of the chi-square test: since Q as computed from Eq. E1 is less than the 95th percentile value of 36.4, one cannot say that there is a statistically significant difference among the number of passengers for each individual cell in Table 32 who will use the offsite airport facility. In short, if the sample size is 10 persons per cell (or a total of 250 passengers), there is no significant difference among the number of passengers who will use the offsite airport facility for each of the 25 market segments shown in Table 32.

Applying Table 32 to Market of 2,225 Total Passengers

As the sample size, or number of passengers per cell, increases, so does the value of Q. The point at which Q exceeds the 95^{th} percentile value of 36.4 is when there are 89 passengers per cell (or 25 x 89 = 2,225 total passengers considering the use of the offsite airport facility). With 89 passengers per cell, application of Eq. E1 yields 36.5, which exceeds the threshold value of 36.4.

$$Q = \frac{(41\%(89) - 50.37)^2}{50.37} + \frac{(47\%(89) - 50.37)^2}{50.37} + ... + \frac{(49\%(89) - 50.37)^2}{50.37} = 36.5$$

Thus, with a sample of at least 2,225 passengers, evenly distributed among the cells, there will be a statistically significant difference in the number of passengers willing to use the offsite airport facility. One practical implication is that based only on the percentages in Table 32 and assuming the same number of passengers in each market segment, the sample size must be at least 2,225 in order for there to be a statistically significant difference in the number of passengers using an offsite airport facility for the various market segments.

Comparing Binary Logit Model and Cross-Classification Model

The cross-classification results of Table 34 showed greater variation than the binary logit results of Table 32. A chi-square test shows that a sample size of 33 passengers per cell (for a total sample of 33 x 25 = 825 passengers) will yield statistically significant differences in the number of passengers using the offsite airport facility. Table 32 required a larger sample size of 89 passengers per cell or a total of 2,225 passengers.

A Caveat to Using Eq. E1

This discussion presumed the same number of passengers per cell. However, at the airports studied, there were different numbers of passengers per cell; e.g., as was shown in Table 36, there were 29 passengers in the VAR 1, FDT 1 market segment but 56 passengers in the VAR 1, FDT 2 market segment. When the different numbers of passengers are taken into account in this fashion, the chi-square test for the binary logit model in Table 32 shows a statistically significant difference with a sample size of at least 78 total passengers.