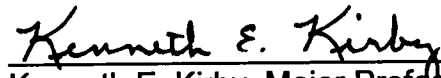
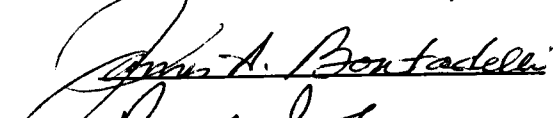
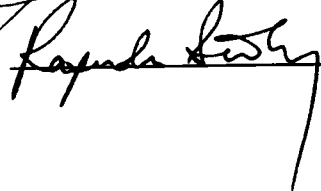


To the Graduate Council:

I am submitting herewith a thesis written by Brad Greene entitled "Predicting the Profitability for a Retail Branch Location Using Simulation Combined With Cluster Analysis." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial Engineering.


Kenneth E. Kirby, Major Professor

We have read this thesis
and recommend its acceptance:

Accepted for the Council:


Associate Vice Chancellor and
Dean of the Graduate School

Predicting the Profitability for a Retail Branch Location Using Simulation Combined With Cluster Analysis

**A Thesis
Presented for the
Master of Science Degree
The University of Tennessee, Knoxville**

**Bradley Mullins Greene
August 1998**

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Abstract

The purpose of this research is to show how simulation combined with cluster analysis can be used to enhance the current methods of location analysis for the banking industry. A simulation model is presented and is validated using data from 14 branch locations. The actual number of customers per cluster that utilized each location serves as inputs into the model. The outputs of the model are profit per quarter and number of each product used. The simulated outputs are then compared to the real profits and product usage of a specific location to investigate how closely the model would predict real profitability and product usage.

In predicting the performance of a future location, an estimate of the number of customers that will use a location is necessary. This research presents several of the current techniques for estimating the number of customers that will use a given location. These techniques can then be used to provide input into the simulation model to provide a more robust location model. In particular, a location model is discussed that combines Geographic Information Systems, gravity modeling, and multinomial logit, with simulation and cluster analysis.

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Chapter 1: Introduction

Forecasting is fundamental to every business organization. Since the beginning of commerce, merchants have tried to predict which products will sell and how much of each product customers will want. The need for forecasting is driven by the fact that resources are scarce and it takes time to garner those resources. Scarce resources mean that there is a cost associated with their utilization. It is desired then to incur this cost only when there is enough demand to justify it. Because there is always some amount of time associated with garnering the necessary resources, it is necessary to attempt to predict what the demand will be at some point in the future when the resources will be in place to supply the given demand.

The banking industry is no different from other industries when it comes to the need for forecasting. One of the most important decisions to be made in this industry is the decision of where to locate future branches. This decision is usually based on the predicted profitability of a specific location. In order to predict the profitability of a location it is necessary to understand the consumer decisions that create that profit. These decisions include whether or not to use a particular location, which accounts or products to use, and how much money to invest in the chosen accounts. The bank must gain an understanding of the variables affecting the outcomes of these decisions by using past data combined with knowledge of one's own organization. These variables can then be manipulated to provide a prediction of the profitability of a given location.

The inherent problem with forecasting is that no one can truly see into the future. The best that can be done is to use yesterday to try and predict tomorrow. For this reason, the goal of any forecast model should not be to predict the future with pinpoint precision, but rather to provide valuable information on the possibilities that the future holds along with the probabilistic risks that accompany each possibility.

Objective

The objective of this thesis is to show that the use of simulation combined with cluster analysis can be used to predict the range of profitability for a given retail banking branch location.

Scope of Thesis

There are five major sections to this thesis:

- Chapter 2. Review of literature on the most used techniques for predicting who will utilize a specific location. Any of these techniques can be used to provide the necessary inputs into the new model.
- Chapter 3. Presentation of a model for predicting the profitability for a retail banking branch in a specific location.
- Chapter 4. Presentation of the validation process that was used on the model.
- Chapter 5. Discussion of how to best to use this model.
- Chapter 6. Discussions of opportunities for further research and improvements that can be made to the model.

Statement of Non-Disclosure

The simulation model to be presented in this thesis was developed specifically for a regional bank. Due to the sensitivity of some of the information used in the model, every effort has been made to present the information generally or when necessary, disguise proprietary information.

Significance of Research

The significance of the model described in this thesis is that it represents a unique use of a very applicable tool, to solve a problem that the tool is seldom used to solve. The model was built using an operations research tool called simulation. The inputs to the model are consumer profiles built from customer data in which the consumers had been categorized geo-demographically into marketing clusters. Traditionally, simulation has been used most frequently to build models for manufacturing. In this case, simulation is being used to model the random behavior of bank customers. This thesis serves as an illustration of how simulation can be used to solve classic marketing problems.

Chapter 2: Concepts and Literature Review

Simulation

Simulation is “the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behavior of the system and/or evaluating various strategies for the operating of the system.” (Pegden, Shannon, and Sadowski 1990, 3) Simulation is a very powerful tool that allows the user to build stochastic models, which can be run on the computer. Because the experiments are run on the computer, it is feasible not only to run an unlimited number of scenarios for sensitivity analysis, but also run those scenarios for many replications in order to generate intervals about the mean and/or standard deviation of a specified measure. In the forecasting scenario this is very useful, because simulation can provide the decision-makers with a range of possibilities rather than a point estimate. This is valuable information because the decision-maker can better understand the risk involved with each alternative.(Taylor 1991)

Fundamental to most simulation packages is a sampling technique known as Monte-Carlo sampling. The Monte-Carlo technique is used to choose the values of the random variables used in the simulation. This technique produces artificial data based on the random number generator and the cumulative distribution of interest. For instance, if it was determined that the sales generated by a certain type of customer followed a normal distribution with a mean of \$100 and standard deviation of \$10, then the random number generator

would generate random values that fell within this distribution. The artificial data that is produced would be normally distributed with a mean of \$100 and standard deviation of \$10. (Pegden, Shannon, and Sadowski 1990, 12)

When comparing simulation to other methods of modeling, it is important to note that simulation is not designed to generate optimal solutions. Instead, simulation helps the user develop intuition about the behavior systems that surround them. It is this enhanced understanding of the system that aids in the decision-making process. In many cases, the mathematical models used to solve for optimal solutions to complex problems are difficult and require so many assumptions be made that a simulation model is more appropriate. (Pegden, Shannon, and Sadowski 1990, 9)

Simulation in Banking

Simulation has been used as a tool in banking for the last ten years. However, true to its reputation as a conservative industry, banks have not fully embraced simulation as of yet. On the operations side of the industry, discrete event simulation is being used to optimize teller service by evaluating different queuing disciplines. In 1987, Dr. Pamela Coats of the Florida State University used simulation in conjunction with artificial intelligence to build software that allows a bank to assess the economics of electronic money networks. According to the literature, however, the most common use of simulation in the banking industry is interest rate risk simulation.

One of the fundamental challenges that faces the banking industry is predicting how changes in interest rates will affect the assets and liabilities of the

organization. Interest rate risk management is the very backbone of any banking institution. The traditional method for evaluating interest rate risk is gap analysis. Gap analysis evaluates the percent difference between all assets and liabilities of a bank. Assets and liabilities are divided between those with a maturity of less than one year and those with long term maturity. The standard method of calculating the potential loss or gain in interest margin is to multiply the total assets (short and long term) by the projected change in the interest rate and the gap-to-assets ratio (positive or negative). (Savings Institutions June 1988)

Many of the critics of gap analysis are proposing that simulation is a better tool. Frederick Chapey states that one problem with traditional budget and planning models is that they assume that financial prices can be forecasted, while simulation provides a stochastic model displaying the probability of an occurrence as opposed to trying to predict a given event. (Chapey 1996, 24)

According to Dr. James Baker, the chairman and president of a broker-dealer-investment advisor based in Oklahoma City, James Baker & Co., the role of simulation should be used to analyze the changes in gap. Banks can simulate different rate change scenarios, and observe how it affects the gap as well as the bottom line. The real strength of a simulation study is that the results provide a range of possibilities and the probabilities associated with each possibility. This gives the decision-makers much more information with which to develop strategies. (Savings Institutions June 1988)

Simulation is also being used by some to optimize the pricing of adjustable rate mortgages. A model developed by the Federal Home Loan

Mortgage Corporation uses Monte Carlo simulation to generate random interest rate scenarios. The technique can be used to generate thousands of possible interest rates, or the user can select a group of interest rates that represent likely scenarios. (Carroll 1989, 69-74)

Other applications for simulation in banking are mentioned briefly in the literature. Some of these are:

- 1) Simulation used to estimate the level of cannibalization of existing product with the introduction of a new product (Hargrove 1988, 28).
- 2) Simulation used to forecast the effect of raising or lowering different parameters for products such as annual credit card fees, mortgage rates, CD rates, etc. (Lingle 1995)

Cluster Analysis

Cluster analysis is a fairly recent method of market segmentation. This method groups consumers according to some specific criteria or set of criteria. Clusters were first used to classify households using geo-demographic data such as household location, age, age of children, etc., as the major criteria. The main assumption used in these cluster analyses is that people who live in close proximity (e.g., neighborhood) to one another, will tend to have similar consumer behavior patterns. Clusters are now grouped by dozens of different criteria, however, most grouping criteria fall into one of four: 1) demographics – age, race, size of household, 2) socio-economics – job classification, education levels, 3) housing – property values, percent of home ownership, 4) location environment – rural, urban. (Deutsch 1992 ,15)

One Chicago-based bank uses credit data in a cluster analysis for financial institutions. Information about 35 specific complex credit characteristics on individual consumers is gathered from a large database. Some of the thirty-five characteristics used in the analysis include number of accounts, type of accounts (such as bank installment, finance, retail), age of accounts, dollar amount of credit, credit utilization, payment histories and public record information. Twenty-five separate spending and payment behavior patterns pertaining to the use of credit were found in the analysis. One use of the cluster analysis is to determine which group of consumers would most likely respond to direct mail marketing. This eliminates costly postage to those individuals that will probably not respond anyway. The rationale behind using credit information to build clusters rather than just geo-demographic data is that the clusters are built around characteristics that directly affect the desired consumer behavior and not just indicators of behaviors. (Ibis 1991, 39,40,41)

Lisa Yorgey, in an article in Target Marketing, describes software that helps in developing clusters. The software builds clusters at three different levels. First, the software uses geo-demographic data to model households from 50 different neighborhood types. The second level builds clusters based on a household's affinity for products from 56 general categories. Finally, the software builds clusters based on the household's propensity to buy 517 specific product and brand preferences. The combining of geo-demographic data with specific marketing data provides the marketing group much more information than using one or the other.(Yorgey 1995, 22)

Location Analysis

Location has always been perceived as a very important factor in the success of a retail market. Because of the importance of location, there is a tremendous amount of research in the area of location analysis. Much of the research on location analysis is geared toward estimating who will utilize a specific location. The objective of presenting the location analysis research is that any of these techniques or a combination thereof, can be used to provide the inputs to the model that will be presented later in this thesis.

According to Boufounou, the primary location model used by banks and most retailers is the analog model. The analog model uses historical data and the demographics of the proposed area (including the area neighborhoods and businesses) to forecast the drawing power of a particular site. The parameters to be included in the model are given different weights or percentages based on the modeler's intuition as to how important each parameter is. Competition and other factors that would detract from the location's overall usage are included in the model as negative weights. The modeler then determines the overall draw area by sketching homocentric circles around the proposed location (Boufounou 1995, 393). The popularity of the analog model is due mostly to its ease of application, however the drawback of the model is that it is extremely subjective. The subjectivity manifests itself in the weighting decisions as well as the estimated impacts of competition, market share, demographics, and distance (Rogers 1987, 42).

Gravity models are another popular location model for banks and retail outlets. Most gravity models take into consideration three factors:

1. The size of the proposed site and the competitors' sites in the area
2. The distance of a potential customer to the proposed location
3. Population distribution and density of the draw area (Rogers 1987, 42)

The gravity model is less subjective than the analog model, however it too has its critics. Boufounou states that gravity models can theoretically model alternative total network configurations, but lacks power when used to evaluate one new site at a time (Boufounou 1995, 393). According to Boufounou, gravity models are difficult to calibrate and can only provide local optimum solutions.

The gravity model, however, is flexible enough to be modified. Okoruwa, Nourse, and Terza, used a gravity model with Poisson arrivals in conjunction with economic and demographic attributes of shoppers to build an improved gravity model for estimating the number of shopping trips taken to the different retail centers in a particular area. They combined this data with historical data on revenue per shopping trip for a given shopping center in order to estimate retail sales for the shopping centers. (Okoruwa, Nourse, and Terza, 1994, 86)

A third method of modeling locations is based on decision theory. The multinomial logit model is used for a variety of different applications, but the literature on location models did not even mention this model. The multinomial logit model (MNL) was recommended as the model of choice in an interview with Dr. Bruce Ralston, a professor of geography at the University of Tennessee at Knoxville.

The multinomial logit model uses the characteristics of the decision-maker (ex. age, sex, house-owner, etc.) and the characteristics of the alternatives (distance from location, competition in area, services, etc.), to build the parameters for a probability model. The model represents the probability that the decision-maker finds more utility (U) in one alternative over the others. The utility of an alternative is defined as the representative components (definable attributes) of utility (V) (e.g., consumer distance from location, household income, etc.) plus an error term (ε).

The assumptions necessary to use the multinomial logit model are that the error terms for each alternative are 1) independently distributed, 2) identically distributed, and 3) Gumbel- distributed with a location parameter η , and scale parameter $\mu > 0$. (Note: the Gumbel distribution is an approximation of the normal distribution with heavier tails; it is used to simplify analysis.)

On the next page is the equation for the multinomial logit model. The numerator represents the components of utility for the chosen alternative i . The denominator is the sum of all alternatives' definable components of utility. The bulk of the work required to build a logit model is in collecting and analyzing the data for the coefficients (β) for each of the attributes that make up the utility for an alternative. Determining values for the coefficients requires collecting sample data for the attributes to be included in the model. For example, a bank would need to collect data on how distance affects a consumer's decision on branch utilization by polling consumers who bank at different branches (both their own

Multinomial Logit Model

$$P_i = \frac{V_i}{\sum_{j=1}^J V_j} = \frac{e^{\sum_{n=1}^N \beta_n x_{in}}}{\sum_{j=1}^J e^{\sum_{n=1}^N \beta_n x_{jn}}}$$

where P is the probability that decision maker h chooses option i and

Notation

i = current alternative

j = 1..... J alternatives

n = 1..... N attributes of alternatives and decision makers

β_n = Coefficient for n th attribute, to be estimated

x_{jn} = Value of n th attribute for alternative j , based on input data

V_i = Components of utility for current alternative

V_j = Components of utility for all alternative j

and competitor's branches). The next step is to solve for logit maximum likelihood estimates using the Newton-Raphson method. These estimates then become the coefficients (β). The inputs (x_j) for the model are the attributes of the prospective customer with respect to each alternative such as, the distance from each of the alternative branches. The output of the multinomial logit model is the probability that each alternative is chosen by that customer.

The most recent development in the area of location analysis is the introduction of geographical information systems (GIS). Geographic information systems as described by Barnett and Okoruwa are, "powerful computer-based tools for integrating and analyzing spatial data from multiple sources." Basically, GIS allows the user to map multiple databases of information. The databases can contain demographic, economic, or other marketing or logistical data. GIS simply takes the data and puts it into the visual format of a map.

There are many applications for GIS technology. UPS uses GIS to determine optimum routings for their trucks. The program optimizes routes by distance, traffic patterns, and stops. A police department in Tacoma, Washington uses GIS to build a map that displays the distribution of crimes to different parts of the city. This map helps the department deploy the police officers in the areas that they are needed most. Verdi Ryan Associates uses GIS to plot the locations and trade areas of a network of branches. By mapping this information, the bank can see the overlap of trade areas, and make strategic decisions about the strength of their branch network. (Dunn 1992, 14)

One of the many applications for GIS technology is location modeling. By combining demographic data with geographic data of an area, the modeler can visualize potential profitable locations. GIS can be used to develop intuition on how a bank's customers use their branches (Dunn 1992, 14). For instance, a database containing information on the location of clusters of customers and potential customers throughout the city could be mapped and used to evaluate potential locations. Areas of a city could be evaluated for their cluster mix or distribution. This information would be especially useful if the bank had an idea of what mix or clusters tend to be most profitable.

Chapter 3: Explanation of the Simulation Model

The model was built using the simulation software Arena[®]. Arena[®] is a combination of the two software packages Siman[®] (which is the simulation programming language allowing the user to build both the model and experiment) and Cinema[®] (which is the software that allows the user to animate a Siman[®] program). Arena[®], which was developed by Systems Modeling Corporation, not only combines Siman[®] and Cinema[®], but also provides a graphical interface making it much more user friendly.

Logic of Model

The model itself is a very simple simulation model as can be seen by the flowchart in Figure 1. The first part of the model involves the entrance of the customer. This is more for the purposes of the simulation model than a depiction of real time. The model creates an entity every time unit simulating a customer entering the system every time unit. We are interested in the total amount of active customers at a particular location over a given period of time, so the length of the simulation is the total number of active customers (ex. If 1200 people were to use a location then the length of the simulation would be 1200 time units).

As a customer enters the simulated system a cluster attribute is generated for that customer. The cluster attribute is a number between 1 and 32 describing to what cluster the customer belongs. The number for that particular customer is randomly chosen from a discrete probability distribution representing the mixture

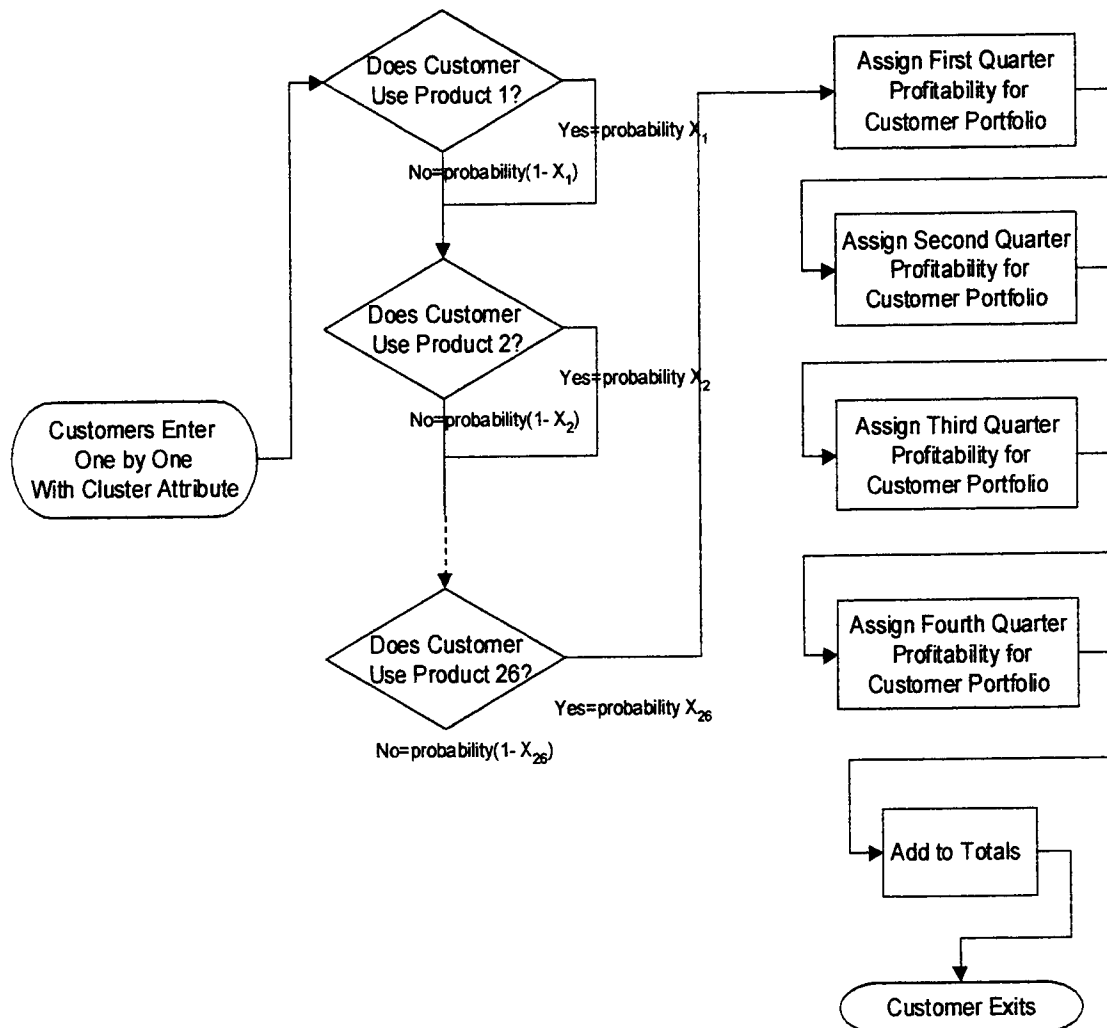


Figure 1: Flowchart of logic for simulation model

of projected customers for that particular location. For example, the cluster mix at a location might be represented by: 5% of customers will be from cluster 1, 3% from cluster 2... 6% from cluster 32.

For purposes of validating the model the assignment of the cluster attribute is based on the percentages of the total amount of active customers at a current branch location, that belong to the specific clusters. If the model is used to forecast a future branch location, then the probability distribution for cluster mix at a location will have to be developed based on an analog, gravity, multinomial logit, and/or GIS model.

The second stage in the model is the assignment of a product portfolio. Each customer entity is assigned a portfolio of products based on the macro-probabilities built from historical data of the entire region (in this case the city of Knoxville). For example, any customer from cluster 1 might have a 45% probability that they would use a savings account, 12% probability that they would use a CD, etc. In many instances, households will have multiple accounts of the same type (e.g. two checking accounts). In order to model this, the customer is assigned the total number of accounts from a discrete distribution which are also built from historical data of the entire region. The assignment of multiple products in this second step is only performed on those products which were initially assigned to the customer.

The final stage of the model is the assignment of profit. Each product in the customer's portfolio is assigned a normalized profit for each quarter based on probability distributions built from historical data taken from the entire region (the

building of the distributions will be discussed later). The formula for normalized profit is different for each product, and is proprietary information for any bank. After the profit has been assigned it is added to the total profit for each product, as well as the overall total profit for the branch.

Input Data

The real key to any simulation model is the input data. In this case, gathering the data was as simple as downloading the bank's extensive database. The difficulty came in sifting through the plethora of data to find relevant information. This is one part of the simulation process that would need to be automated in order for this model to be efficient enough to be justified.

An outside consulting firm developed the profiles of the different clusters for banks. The cluster groupings were developed using bank data and geo-demographical data from all across the nation and therefore the clusters are supposed to apply nationally. Theoretically, a customer in cluster 1, living in Pierre, South Dakota should have similar bank behavior to a customer in cluster 1 living in New York, New York.

The bank in Knoxville then took the national cluster profiles and categorized their own database accordingly. It is also important to note that clusters categorize households rather than individual consumers (in the simulation model each customer represents a household). This is because financial decisions are often household decisions rather than individual decisions. The assumptions that were used in developing this model are that both the consulting firm and the bank in Knoxville have correctly identified these clusters,

and that the households within these clusters will behave in similar fashions with some degree of randomness. One of the objectives of the model is to characterize the randomness of the consumer behavior within clusters.

Number of Customers

Estimating the total number of households who will utilize a location can be done using any of the methods described in the literature review. As can be seen in Table 1, the most commonly used methods are the analog model, the multinomial logit model, the gravity model and the use of geographical information systems. It is my opinion that the best complement for the simulation model is a combination of the multinomial logit and gravity models with the use of GIS.

Table 1: Inputs required for the simulation model

Inputs	Format of Input	Origin of Input
Total number of customers	Number estimate	GIS, gravity model, multinomial logit, etc.
Product profiles of each cluster	Probability of a customer from a specific cluster using a specific product	Historical data
Profit distributions for each product for each cluster	Probability distribution	Historical data

Once the attributes and their coefficients are determined in the multinomial logit model, it could actually be written into the simulation model. The attributes typically used to build gravity models (size of the branch, and distances from the branches) will become attributes in the logit model. A model built using GIS could be used to develop information on the draw area. A GIS map of the cluster

mix of potential areas would provide some of the attribute inputs (x_j) into the logit model.

The accurate prediction of *who* and *how many* will use a potential location is critical to the accuracy to the overall forecast. The variables that make up this portion of the forecast are dynamic and hard to predict. However, while the bulk of the research on location analysis has been on the prediction of *how many* will use a location, very little research has been done on *how* the customers will use the potential location. The emphasis of this model is on predicting how customers will use a potential location. This leads to the second and third inputs, the product profiles and the profit distributions, both of which provide the engine for the simulation model.

Product Profiles

The probabilities for the product profiles of each cluster are simply the ratio of total number of accounts using a product to the total number of customers in that cluster. In the model, these product profile probabilities are used to determine which products a given customer will use. Each customer is assigned a cluster and then a product portfolio. For example, if 34 out of 100 households in the city from cluster 1 had a savings account then the probability that a new household from cluster 1 would use a savings account would be 34%. As seen in Table 1, the product profiles were developed using historical data, and the sample space used to build these probabilities was the 1996 database made up of all active accounts of a regional bank for the city of Knoxville and surrounding areas.

The assumption that is made when developing the product profiles is that the choice of one product is independent of the choices of other products.

Intuitively, this is not valid assumption (e.g. person might choose between a CD and a savings account, depending on the interest rates). However, one year of data is not enough to determine if the correlation coefficients between products are significant enough to include in the model. Therefore, the model assumes independent product choices, while recognizing this as a potential source of model error.

Profit Distributions

The third piece of input data used in the model is the profit distributions for each product for each cluster. For all thirty-two clusters, each product has four quarters of normalized profit data. It was determined to identify a profit distribution for each of the four quarters, because there are seasonal trends associated with the usage of most products.

The first step in the process of building profit distributions is to develop histograms for each of the streams of data. For instance, all of the historical data on normalized profits for savings accounts for cluster 1 is placed into a histogram. This can be seen in Figure 2. The histogram is then used to approximate a probability distribution, such as the normal distribution. The Arena® software package has an Input Analyzer that is used to build the histograms and approximate probability distributions. The software uses three goodness of fit tests to help the user determine which of the given distributions

Distribution Summary

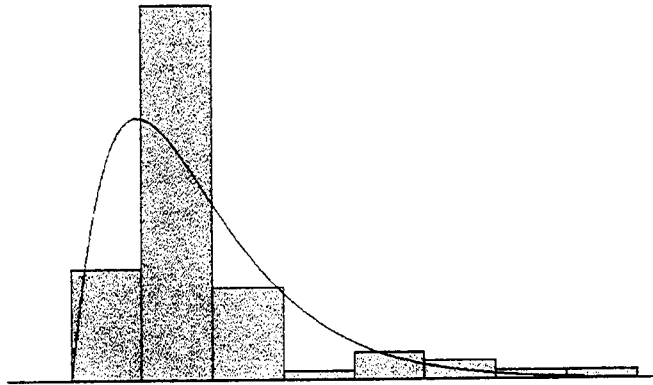


Figure 2: Histogram being fit to a probability distribution

Distribution: Gamma
Expression: $-122 + \text{GAMM}(97.4, 2.07)$
Square Error: 0.074455

Chi Square Test
Degrees of freedom = 1
Test Statistic = 18.3
Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
Test Statistic = 0.158
Corresponding p-value = 0.054

(Beta, Erlang, Exponential, Gamma, Lognormal, Normal, Triangular, or Weibull) fits the best. The three tests are 1) means squared error test, 2) Kolmogorov-Smirnov Test, and 3) Chi-Square test.

Most of the data sets have enough data samples to build distributions that fit one of the eight distributions well. There were, however, some distributions that did not fit any of the distributions well. In most cases the reason for the lack of fit was an insufficient number of data points to establish a pattern. In these cases, the best distribution was fit anyway with the knowledge that these anomalies would most likely contribute to the overall error of the model.

However, the fact that there was an insufficient amount of data points to build an accurate distribution means that the probability that a household within that particular cluster would use that product is small, so that the error contribution will most likely be negligible.

Table 2 is an example of the product profiles and profit distributions for cluster 24. The data under the column labeled, "% of Total" are the probabilities that a person from cluster 24 will choose to use each of the products one through ten. The data under the columns labeled "Norm (x) Profit Distribution", where $x = 1, 2, 3, 4$, are the probability distributions for cluster 24 for the profit of each product for each respective quarter. This data represents all of the customers of cluster 24 in the Knoxville area.

Table 2: Product probability and profit probability profiles for Cluster 24

CL	PROD	COUNT	% OF TOTAL	NORM PROFIT (1) DISTRIBUTION	NORM PROFIT (2) DISTRIBUTION	NORM PROFIT (3) DISTRIBUTION	NORM PROFIT (4) DISTRIBUTION
24	1	484	0.1415	-114 + LOGN(250, 283)	-120 + LOGN(263, 236)	-113 + 2.87e+003 * BETA(0.573, 5.97)	-170 + LOGN(304, 232)
	2	519	0.1518	-17 + LOGN(23.6, 20.7)	-14 + LOGN(21.1, 17.9)	-15 + LOGN(18.2, 12.4)	-15 + LOGN(17.5, 10.5)
	3	514	0.1503	-9 + 223 * BETA(0.663, 2.67)	-9 + 225 * BETA(0.4, 2.04)	-9 + 225 * BETA(0.375, 2.16)	-9 + 223 * BETA(0.366, 2.44)
	4	2201	0.6436	-65 + LOGN(75.2, 39.4)	-68 + LOGN(95.3, 43.9)	-88 + LOGN(112, 42.3)	-84 + LOGN(105, 38.9)
	5	374	0.1094	-96 + LOGN(153, 141)	-64 + LOGN(79.2, 69.4)	-92 + LOGN(109, 59.4)	-59 + LOGN(77.1, 53)
	6	243	0.0711	-8 + WEIB(26.3, 0.863)	-6 + WEIB(28.2, 0.892)	-6 + LOGN(31.5, 57.8)	-6 + LOGN(29.5, 52.7)
	7	434	0.1289	-11 + LOGN(146, 236)	-11 + LOGN(130, 207)	-10 + LOGN(128, 242)	-10 + 1.15e+003 * BETA(0.508, 5.05)
	8	226	0.0661	-194 + 3.18e+003 * BETA(0.611, 4.83)	-38 + 688 * BETA(0.584, 3.11)	-33 + 574 * BETA(0.452, 2.23)	-37 + 453 * BETA(0.459, 2.19)
	9	330	0.0996	-44 + LOGN(118, 147)	-43 + LOGN(101, 95.5)	-38 + LOGN(95.5, 103)	-34 + LOGN(94.9, 112)
	10	1487	0.4348	-39 + 1.89e+003 * BETA(0.368, 11.3)	-33 + 1.66e+003 * BETA(0.42, 12.9)	-30 + 1.84e+003 * BETA(0.338, 12.3)	-55 + LOGN(70.5, 31.9)
#CUST=		3420	8812				

Chapter 4: Model Validation

Validation is the determination that the simulation model is an accurate representation of the real system. In the case of the bank simulation, it is necessary to test the forecast of the simulation model for a given period against the real performance of a branch location for the same period. This way the model can be tested to determine how well it would have predicted the resulting performance of a branch at a given location.

Fourteen current branch locations were used to test the model. These locations were chosen at random, and represent different sections of the city of Knoxville. For purposes of simplification, ten of the bank's twenty-six products were used in the study. The ten products, however, do represent 99.7% of a branch's profits and 93.7% of the branch's activity. The model was run using as inputs the total number of customers who held active accounts during the time of the study, and the probability distribution of the customers' clusters. If the model were being used to determine the profitability of a future branch location these pieces of information would also have to be predicted using the location models that have already been discussed.

The distributions for product usage and profitability were developed using data from the entire city of Knoxville. These macro-distributions provide the engine for the simulation model. The number of households by cluster that utilize a specific branch are the inputs to the model, which is then used to predict the performance of the branch location.

The output measures used in the study are quarterly profit for each product and total number of each product used. The simulation model represented one year of operation. Each simulation was run or replicated thirty times. For each of the fourteen locations, thirty replications were analyzed to determine the mean and standard deviation by product, for each of the five output categories (four quarters of profit and total number of product used).

The test used to validate the model was regression analysis. If the model is a good forecast model, then the real value for each random variable should be equal to the predicted value for each random variable (e.g. actual branch profit = average simulated branch profit). Given that this is true and we plot the values of the predicted random variables (x-coordinates) for each branch versus the real random variables (y-coordinates) for each branch, on the x-y Cartesian plane, then the result should be a straight line with slope equal to 1. This can be seen in Figure 3. It stands to reason that we can use regression analysis to compare the predicted random variables to the real random variables. If the plots show a strong tendency towards a straight line with slope equal to one, then the model proves to be a good predictor.

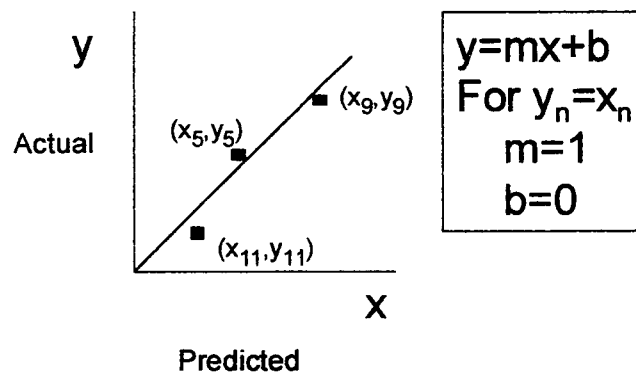


Figure 3: Validation using linear regression

Table 3 shows the results of the regression testing. The most significant test results in each of these charts are the R square value and the slope of the fitted line. The F-ratio and its corresponding p-value (Prob>F) are minimal tests of fit. The slope of the fitted line is the first test for validation of the model. If the slope is not close to 1, then it really does not matter if the other tests of fit are significant. The R square value measures the proportion of variation accounted for in the linear model. The closer the R square value is to 1, the better the model fits. If both the slope of the line and the R square are close to 1, then there is evidence that the model is a good predictor.

The F-ratio tests the hypothesis that all of the points actually came from the regression line. If the hypothesis is true then the difference between the line and points off of the line is assumed to be due to naturally occurring variation. The p-value associated with the F-ratio indicates the probability that an F-ratio that was bigger could happen by pure chance. A p-value of less than 0.05 is considered evidence of a regression effect. (Montgomery 1994)

Table 3: Slope, R square and p-value for linear regression analysis for validation

Product Usage				Total Profit			
Product	Slope	R square	Prob(>F)	Quarter	Slope	R square	Prob(>F)
1	1.065	0.874	0.00000	1	0.891	0.863	0.00000
2	0.947	0.866	0.00000	2	0.988	0.907	0.00000
3	1.143	0.845	0.00000	3	0.988	0.910	0.00000
4	1.027	0.963	0.00000	4	1.003	0.891	0.00000
5	0.830	0.632	0.00040				
6	1.037	0.754	0.00003				
7	1.091	0.872	0.00000				
8	1.191	0.455	0.00583				
9	1.112	0.804	0.00001				
10	0.973	0.970	0.00000				

Table 3 shows the results of regression tests for the individual product usage and total profit per quarter. The product usage (how many accounts of each product were open at a particular branch) predictions show a varying degree of success from the model. Products 1, 2, 4, 6, 7, and 10 prove to be predicted well by the model. The slopes of the fitted line for each of these products are within ten percent of 1, and the R square values indicate that most of the variation can be explained by the linear model. Products 3, 5, 8, and 9 (in particular 5 and 8) are not predicted as well by the model. While none of the slopes of the fitted lines are beyond twenty percent of 1, there is enough error in the model to be of concern. The bigger concern is of the R square values for these products. In products 5 and 8 the R square values indicate that there is a lot of variation that cannot be explained by the linear model. This indicates that there are several predicted values that differ significantly from the actual values.

The results of the regression tests for total profit per quarter indicate that the model is a good predictor of total profit. The slope of the fitted line for first quarter profits is the only one of the four that is not within ten percent of 1. The only reason that this might be of concern is that the other three quarters are so close to 1. The R square values for all four quarters indicate that the linear model can explain most of the variation. Therefore it is concluded that this model is a good predictor of total quarterly profit of a branch.

It is interesting that while the usage of only six of the ten products can be predicted well with this model, the aggregate total profit for all four quarters is very predictable. The reason for this is that the six products that are very

predictable represent more than 75% of the profit and product usage. The two products (5 and 8) that are least predictable represent less than 10% of the profit and product usage.

Based on these tests for model validation there is evidence to believe that the simulation model is an appropriate model to predict the performance of a branch location. The model is by no means perfect, and there is room for improvement, which will be discussed in Chapter 6.

Chapter 5: Simulation as a Tool for Location Analysis

Simulation is a valuable tool for modeling stochastic processes. It can provide not only a point estimate of a random variable but the variation associated with that random variable. Simulation does have its drawbacks. Often the data required to build an adequate simulation of a system is intensive. Simulation modeling is more art than science, requiring a skilled programmer who also has adequate knowledge of the system to be modeled. The simulation process is also very time consuming. Before electing to use simulation as a location analysis tool, the user must decide if the information to be gained from simulation warrants the investment in time and resources.

The bulk of the time required to build the simulation model can be attributed to sifting through the mountains of data. Banks are unique marketing organizations, because they are privy to large amounts of good information on their customer base. Therefore, there is a significant time investment to be expected in building a branch location simulation. However, once the projected customer engine (using either a gravity, multinomial logit, or GIS model or combination thereof) and the profit engine (the regional product profiles by cluster and the profitability distributions found in Table 1) of the simulation are built and validated, the analysis of the results is straightforward and quick. The maintenance of the model requires that the profit engine is updated once a year if not quarterly. However, much of this can be automated by anyone with database programming skills. The logic of a branch location simulation is very simple, as

can be seen in the flowchart in Chapter 3. The time required for programming the model is small relative to the time required for data manipulation and validation.

With all of that said, the power of combining simulation with cluster analysis and/or one of the three location analysis tools previously discussed, does justify the investment in time and resources. The two reasons that the investment is justifiable are: 1) this method of location analysis is more thorough and takes into account more variables than any of the location analysis tools by themselves, and 2) this model is robust and has more applications than just location analysis.

Simulation and Cluster Analysis as Location Analysis Tools

There are two major variables that affect the profitability of a particular branch location: 1) the number of customers and 2) the consumer behavior of the customers who choose to use a particular branch location. The focus of the traditional location analysis tools is on the first variable. These models generate predictions of how many people will utilize a particular location and then multiply that number by aggregate information on the average profitability per customer. The problem with these models is the assumption that all customers are equal.

Table 4 shows two branches, one with 2,030 total customers and one with 1,915 total customers. The branch with fewer customers generated almost 50% more profit than the branch with more customers. The second column shows the average profit generated by a customer from a given cluster. Branch 2 has a larger percentage of customers that generate higher average

Table 4: Comparison of two branches and their cluster mix

Cluster	Avg Profit per Customer	Percent of customers Branch 1	Percent of customers Branch 2	Number of customers Branch 1	Number of customers Branch 2	Actual Profit (\$) Branch 1	Actual Profit (\$) Branch 2	Percent Profit Branch 1	Percent Profit Branch 2
1	370	0.6%	3.1%	13	59	4932	22700	0.9%	2.6%
2	693	0.5%	5.8%	11	112	7718	79565	1.3%	9.3%
3	0	0.0%	0.0%	0	0	0	0	0.0%	0.0%
4	514	1.4%	13.7%	29	263	14904	147164	2.6%	17.2%
5	0	0.0%	0.0%	0	0	0	0	0.0%	0.0%
6	292	0.0%	0.1%	0	2	0	585	0.0%	0.1%
7	215	0.0%	0.1%	1	2	1279	3898	0.2%	0.5%
8	264	0.1%	1.7%	3	33	2302	24118	0.4%	2.8%
9	317	0.9%	5.7%	18	109	5706	44577	1.0%	5.2%
10	266	0.1%	1.4%	3	26	785	7921	0.1%	0.9%
11	322	0.3%	0.9%	6	17	1943	6480	0.3%	0.8%
12	250	0.1%	0.4%	2	7	813	4864	0.1%	0.6%
13	297	20.5%	9.7%	416	185	123368	55861	21.4%	6.5%
14	457	2.6%	11.4%	52	219	23995	110090	4.2%	12.8%
15	320	2.4%	0.9%	49	17	16687	7442	2.9%	0.9%
16	409	2.4%	3.2%	48	62	19639	28336	3.4%	3.3%
17	107	0.1%	0.2%	3	3	336	621	0.1%	0.1%
18	126	0.5%	0.6%	10	11	2257	2383	0.4%	0.3%
19	251	0.8%	0.2%	17	3	4374	754	0.8%	0.1%
20	251	10.0%	4.0%	204	77	53170	25314	9.2%	3.0%
21	154	0.2%	0.3%	4	5	666	771	0.1%	0.1%
22	176	5.6%	2.3%	114	44	21235	9760	3.7%	1.1%
23	235	5.2%	8.9%	106	171	24902	40264	4.3%	4.7%
24	263	31.0%	8.3%	629	159	166589	51870	28.9%	6.1%
25	0	0.0%	0.0%	0	0	0	0	0.0%	0.0%
26	203	8.5%	3.4%	173	65	36253	21188	6.3%	2.5%
27	235	0.2%	0.2%	4	3	951	706	0.2%	0.1%
28	232	1.4%	1.9%	28	36	6420	8345	1.1%	1.0%
29	241	0.1%	2.0%	2	38	1271	43774	0.2%	5.1%
30	279	2.3%	3.1%	47	60	13126	26751	2.3%	3.1%
31	211	0.1%	0.2%	3	4	678	844	0.1%	0.1%
32	569	1.7%	6.4%	35	123	19853	79970	3.4%	9.3%
				2030	1915	576052	856915		

profit. For example, the largest concentration of customers for Branch 1 is in cluster 24. The profit generated by the 629 customers in this cluster is \$166,589. At branch 2, only 263 customers generated a profit of \$147,164. These customers came from cluster 4 whose average profit per customer is almost twice the average profit generated by a customer from cluster 24. All customers are not equal.

Given that different types of customers are of different value to the bank, it is a fair assumption to make that different mixtures of customer types will also provide different value to the bank. Just as in Table 4, Branch 2 and Branch 1 have different customer mixtures and therefore different profitability. Cluster analysis provides valuable insight into the differences between customers. The thirty-two customer types used in the cluster analysis are much more indicative of reality than the traditional three banking market segments (wealthy, affluent, and consumer). However, adding clusters (market segments) adds both information and complexity, thus the need for a tool such as simulation. The true power of simulation lies in the ability to experiment with a system that does not even exist. The experimentation is fast, easy to analyze, and can be easily replicated so as to build information on the stochastic nature of a system. These three attributes make simulation an ideal engine for sensitivity analysis. The ability to replicate experiments also makes simulation the ideal tool to investigate the complexities of different consumer mixtures in a branch location.

Simulation and cluster analysis can be used together to enhance the current methods for location analysis. The current location analysis tools are

used primarily to predict how many customers will use a future location. This information is necessary to predict a location's profitability, however it is incomplete. Using the information provided by cluster analysis, one could not only predict how many customers will use a future location, but who those customers are and how they will behave. The role of simulation is then to provide an experimentation platform as well as to model the natural variation in consumer behavior.

As it was stated before, a very robust model would use the multinomial logit model (using as attributes, characteristics from the cluster analysis and the gravity model among others) combined with a GIS model of the regional cluster mixtures, to provide input into the simulation profit model (also based on cluster analysis). This can be seen graphically in Figure 4. Ideally the logit model would be programmed into the simulation, which would allow for some sensitivity analysis of the variables in the logit model. For instance, the logit model could be manipulated to represent such "what if" scenarios as, "What if the bank targeted a different cluster group in a particular draw area? How would that affect the profitability of this branch location?"

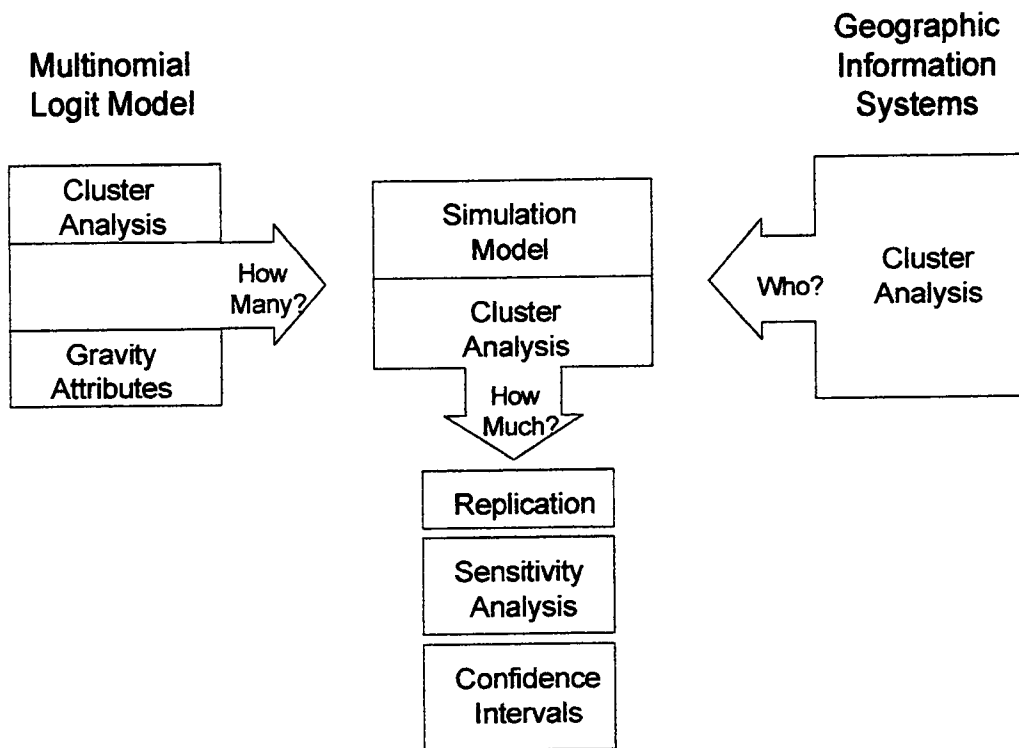


Figure 4: Flowchart of the combination of the multinomial logit model GIS, and the simulation model

Additional Applications for Model

The intended application for the model is to predict a range of profitability for a specific branch location. However, the model is robust and can be used to evaluate other marketing strategies. One marketing strategy that this model could be used to develop is regional or network strategies. For instance, consider a bank that is seeking to expand its network of branches. The bank is not just interested in the profitability of one branch at a particular location, but a network of branches in an area of the city. The bank could use a GIS map with the cluster information of a potential network area to serve as inputs to the

simulation model. Experiments could then be run to determine which areas of a city to target that would have the most profitable customer mix. In the same token, as banks continue to merge and interstate commerce continues to grow this model could be used to evaluate a region of a state, an entire state, or even a region of the country.

Another application of this model is target marketing within a specific location. By understanding the cluster distribution in an area and the products that customers in that area tend to use, banks can tailor their product selection to the clientele. The simulation model can be used to test different scenarios related to product selection schemes. In fact, with some additional effort, the model could be expanded to evaluate the effects of different product promotions (in particular the cannibalization of mutually exclusive products).

Chapter 6: Conclusions

Conclusions

A method for predicting the profitability for a retail branch location is presented in this thesis. The method involves combining simulation with marketing cluster analysis. The advantage of using simulation and cluster analysis is that the model can reflect the different types of consumers that utilize a branch location. The projected customer input to the model can be provided by any of the location analysis tools that are in the literature. The four models reviewed here are the analog, gravity, multinomial logit, and GIS models. It is recommended that the customer input model be a combination of the multinomial logit model (with demographic data from the cluster analysis and size and distances from the Gravity model serving as attributes) and a GIS model. The GIS model should consist of a map of households labeled by cluster.

The simulation model has been validated by comparing the simulated performance of fourteen Knoxville area branches to the actual performance of these branches. A linear model was fit using as x- and y-coordinates the simulated result and the actual result, respectively. The linear models for the total profit per quarter all have a slope approaching one and proved to fit the linear model well. This gives us strong evidence that the model is a good predictor of branch profitability. There is also the potential that the model can be used to evaluate branch networks, regions of states, or regions of countries for profitability potential, as well as to evaluate product mix and promotion decisions at a particular location.

Suggestions for Further Research and Improvements to the Model

The simulation model presented in this thesis represents half of the solution to a location analysis problem. The main area of further research resulting from this thesis is the development of a complementary multinomial logit model to attach to the front end of the simulation. There is a need for research on the attributes that make up the decision to use a branch. How do demographics and cluster information affect the decision? Does the size of the branch matter? The décor? To which cluster does it matter most?

There are several possible reasons for error in the simulation model presented, which need to be investigated. More cluster information is needed to gain truly representative profit probability distributions in some cases. Research needs to be done on bank products in general, as to the probability distribution that best models the profit of a product such as savings accounts. For the existing model the product profiles and profit distributions were built using data on the entire city of Knoxville. Ideally, cluster profiles for product usage and profit distribution should be developed using data from many different sample areas.

Earlier in the thesis the assumption of independence in product choice was discussed. Research needs to be done to determine if there are significant correlation coefficients associated with the customers' choice of products. What was not discussed earlier is a second assumption of independence. The assumption is that profitability within a customer's product profile is independent. All customers have a finite level of money with which they can choose to invest in all of the products in their portfolio. Therefore, the amount chosen to invest in

one product affects the amount of money left to invest in other products. Again, more research should be done to determine how much of the model error can be attributed to this assumption, and how should this information be incorporated into the model, given that dependence proves significant.

A final source of error in the model that represents an opportunity for further research is how to incorporate the effects of the national, state and local economies, interest rates, and product promotions into the simulation model.

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VITA

VITA

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