NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MBA PROFESSIONAL REPORT

Real Estate Site Selection: An Application of Artificial Intelligence for Military Retail Facilities

---

By: **Eric L Shangle**
September 2006

Advisors: **Beck Jones**
Joe San Miguel for John Shank (deceased)

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 2006	MBA Professional Report

4. TITLE AND SUBTITLE:
Real Estate Site Selection: An Application of Artificial Intelligence for Military Retail Facilities

5. FUNDING NUMBERS

6. AUTHOR(S) Eric L Shangle

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943-5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
N/A

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES The views expressed in this report are those of the author(s) and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT *(maximum 200 words)*

The purpose of this MBA Project is to investigate and provide a comprehensive overview of the current real estate site selection industry while showing applications of how artificial intelligence can improve the selection process. The goal is to identify and document both the specific industry practices primarily utilized and the principal uses of artificial intelligent algorithms for site selection and sales forecasting.

The results of this project can be applied to military retail facilities (exchanges and commissaries). The current business model for military retail facilities may not be optimized based upon current trends market data. Optimizing the location and allocation of goods and services through artificial intelligent algorithms can provide previously unrealized cost savings to the Department of Defense.

14. SUBJECT TERMS Real Estate, Site Selection, GIS, Geography, Optimization, Retail, Genetic Algorithm

15. NUMBER OF PAGES
85

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited.

REAL ESTATE SITE SELECTION: AN APPLICATION OF ARTIFICIAL INTELLIGENCE FOR MILITARY RETAIL FACILITIES

Eric L Shangle
Lieutenant, United States Navy
B.S., United States Naval Academy, 1997
M.A., University of Oklahoma, 2002

Submitted in partial fulfillment of the requirements for the degree of

MASTER OF BUSINESS ADMINISTRATION

from the

NAVAL POSTGRADUATE SCHOOL
September 2006

Author: ____
Eric L Shangle

Approved by: ____
Professor Becky Jones

____
Professor Joe San Miguel for John Shank (deceased)

____
Robert N. Beck, Dean
Graduate School of Business & Public Policy

THIS PAGE INTENTIONALLY LEFT BLANK

REAL ESTATE SITE SELECTION: AN APPLICATION OF ARTIFICIAL INTELLIGENCE MILITARY RETAIL FACILITIES

ABSTRACT

The purpose of this MBA Project is to investigate and provide a comprehensive overview of the current real estate site selection industry while showing applications of how artificial intelligence can improve the selection process. The goal is to identify and document both the specific industry practices primarily utilized and the principal uses of artificial intelligent algorithms for site selection and sales forecasting.

The results of this project can be applied to military retail facilities (exchanges and commissaries). The current business model for military retail facilities may not be optimized based upon current trends market data. Optimizing the location and allocation of goods and services through artificial intelligent algorithms can provide previously unrealized cost savings to the Department of Defense.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

First and foremost I would like to thank my parents, Ronald and Barbara, for their continued and unrelenting support throughout the years. The obstacles placed before me have been easily overcome thanks to their help and presence. I love you both dearly. I would also like to thank David Chipman for his patience and unrelenting support through difficult times. Change is inevitable; however it's not always easy. Thank you for making my changes easier.

I would like to show my gratitude to Professor Jones. I respect her professionally and personally. Her tutelage and honesty has enabled me to transcend my previous abilities. She stood by me throughout this entire process. It has been a long road.

Finally I would like to show my respect and thank the late Professor Shank. He continually challenged me. His standards were high and accepted nothing less. Without his willingness to help a lost student, I would not have been able to complete this project. He will be missed.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

A. BACKGROUND

The consumer retail marketplace in the United States has become increasingly more competitive in recent years due to increase communications, online shopping opportunities, a new world order post "9-11", and an on-demand mentality. The proper location of a company's store and allocation of goods can assist or impede store performance. Optimizing these factors should be of utmost importance for real estate site selection. This concept applies to private industry and to the Department of Defense.

Numerous methodologies are used in the private sector to choose real estate for business opportunities. However, many companies do not optimize their selections while utilizing spatial decision support systems (SDSS) to assist in their real estate planning. This is true for the retail, restaurant, banking, and any other industry where store location can drive sales. External factors will affect sales based on location. These factors can be; but are not limited to; location, competition, population, and site characteristics.

Military retail facilities are currently aligned with operational military installations. The methodologies utilized in the private sector can be applied to military retail facilities. The external factors are relevant for both. An emerging approach for managing external factors to optimize site selection utilizes artificial intelligent algorithms. Artificial intelligent algorithms, SDSS, and geospatial information systems (GIS) software have gained popularity for real estate site selection in recent years. This project looks into possible advantages of applying artificial intelligent models to model consumer behavior in an effort to prevent opening non-profitable stores and optimize locations.

B. RESEARCH QUESTIONS

This project is designed to answer basic questions concerning optimizing real estate site selection. Many companies do utilize computer models to assist in their real estate site selection process, however optimizing these results in a market requires further

modeling techniques. The use of computer models utilizing artificial intelligent algorithms to optimize the site selection problem will be shown as an optimal option for this process.

1. Primary Questions

The primary focus of this project is to answer the questions:

- Is there a current need for market planning modeling? If so, why?
- To what extent do artificial intelligent algorithms improve the market planning process?
- Can artificial intelligent algorithms be applied successfully to market planning?

2. Secondary Question

In order to fully answer the primary questions, a secondary question needs to be answered:

- What are the limitations to current market planning models?

C. PROJECT BENEFITS

This project provides insight into the real estate site selection process and its complexities. Previously real estate site selection was a “best-guess kind of game” (Chittum, 2005). This is not necessarily the case anymore. Current techniques in real estate site selection will be discussed showing their advantages in predicting sales. Improved accuracy in assessing a location’s potential sales along with its interaction with current stores can be vital in selecting sites. However, there are limitations to current site selection methodologies. In order to assess sales across an entire trade area or market, further optimization needs to be introduced. This optimization can come from the use of artificial intelligent algorithms. These algorithms can be applied across many industries such as the retail, restaurant, and banking industries.

The results of this project can be directly applied to military retail facilities (exchanges and commissaries). Optimizing the location and allocation of goods and services through artificial intelligent algorithms can provide previously unrealized cost savings to the Department of Defense.

D. METHODOLOGY

An extensive literature review of relevant business, real estate, and technical topics was conducted. Internet sites, testimonies, magazine and journal articles, among others were reviewed. In order to understand current real estate site selection techniques, a historical context is provided. The origin of site selection methodologies was important to understand in order to show the evolution of the site selection process.

In order to optimize sales for a specific trade area, optimization techniques need to be utilized. A review of artificial intelligent algorithms as a form of optimization was reviewed as an option. The evolution of artificial intelligent algorithms is provided in order to show why they are just now becoming a viable option for optimization. Ultimately genetic algorithms are shown in theory to be the optimal artificial intelligent algorithm for optimization purposes.

E. PROJECT ORGANIZATION

This project is organized into five chapters. Chapter I provides an introduction to the objectives of this project. Chapter II provides a literature review highlighting the concepts of real estate site selection and the applications of emerging technologies in the real estate site selection process. This chapter also provides a look into the origins of real estate site selection in business. Understanding the need for site selection analysis led to the research of optimization techniques and methods of delivery. This portion of the chapter discusses how businesses utilize these methodologies today.

Chapter III examines the real estate site selection processes currently used in the private sector. Four main methods of site selection analysis are presented in depth. These methods are examined for strengths and weakness in the approach to providing

accurate results in operation. Real-world examples of relevant methods are provided to show the complexities of this analysis and the results they can afford.

Chapter IV examines the application of artificial intelligent algorithms for optimizing the site selection process. Market planning techniques are examined along with the use of artificial intelligent algorithms in this process. Site selection models alone cannot analyze and entire market on their own. Models will look at one store and its potential interaction in the market. However they will not take into account how all stores and locations will interact with each other. In order to do this, further optimization needs to be conducted. A comparison to traditional real estate site selection techniques is examined showing actual and potential improvements in this process. Real-world examples are provided to show actual effectiveness and improvement from use of artificial intelligent algorithms in practice.

Chapter V summarizes the results of this project. Limitations and conclusions are discussed. Applying the results of this project to military retail facilities is shown as a possible application of optimizing real estate site selection techniques.

II. LITERATURE REVIEW

A. INTRODUCTION

This chapter provides background information on a number of subject areas in order to lay the foundation for topics raised throughout the remainder of this project. As a result of this literature review, a context is created for the analysis of the real estate site selection process. A main goal of the real estate site selection process is to optimize the number and location of sites within a market to provide maximum profit based upon consumer actions and available real estate. Basically, this process will model consumer behavior within a market related to current and potentially available real estate locations. Ultimately there will be an optimal mix of sites that will provide the maximum profit for the company based on these factors. These factors can now be managed through emerging technologies such as SDSS software and artificial intelligent algorithms. The following subject matter will help frame business, management, and technical concepts that can be applied to the real estate site selection process.

This chapter is broken into two main portions: real estate site selection process and optimization using artificial intelligence. First the theory of real estate site selection is discussed. Studies detail the root of the process by discussing the multitude of factors involved. Industry experts highlight specific issues and methods that affect their site selection process. These methods are broken into four main approaches.

A discussion on the use of artificial intelligent algorithms is presented next. Artificial intelligence, specifically genetic algorithms, represents an emerging form of site selection optimization. Looking at one or a few sites in isolation is not sufficient to account for the interactions between sites and consumer actions. Optimization is needed to take into account all factors that could affect the profit for a given market. This section further explains how artificial intelligence can improve site selection beyond traditional forms of analysis.

B. REAL ESTATE SITE SELECTION PROCESS OVERVIEW

Choosing a site to open a new store or business can be related to the success or failure of that store or business. Location and allocation of goods are essential components to a successful new store. This section focuses on research done on the real estate site selection process, current processes currently utilized, and the affected industries.

1. Real Estate Site Selection History

Lea (1989) describes the history of real estate site selection by breaking out three distinct periods leading to modern site selection techniques: the beginnings of retail theory via neoclassical theories (1870-1950), the renewal in site selection with quantitative analysis (1950-1985), and modern techniques using GIS-based analysis (1985-present). Each of these periods represents a shift in methodologies of where commercial real estate would be placed. This specifically affected retail companies.

a. Neoclassical Theories (1870-1950)

The end of the Victorian Period marked the first time in North American history where products were mass-produced for customers. This production allowed many smaller stores to open providing goods from outside the local area. In the 1880's larger distribution centers were appearing in order to supply these more remote stores (Kates, 1997). Locations were being chosen for stores based upon population, but the competitive nature of the retail industry was not apparent.

Larger stores and smaller stores were able to coexist in this time without competitive interaction. William Reilly developed "Reilly's Law" in 1931. This law stated that customers located between two cities would be drawn to the larger city for retail purposes. This applied Newtonian physics to consumer behavior. The attractiveness of the location was related to the distance between the consumer's residences. This idea drove many company's real estate locations during this time. It wasn't until The Great Depression and the two World Wars that competition truly impacted the face of real estate site selection (Kates, 1997). As many goods and services were depleted, store location was becoming more important.

b. Quantitative Analysis (1950-1985)

The post-WWII era in North America represented a time of excess and exodus. The war was over and people were again spending money. People wanted to forget about the troubles of previous years and invest in a new future. Thompson (1966) adds that retail marketing became increasingly important in this period. As men and women exited their wartime occupations there were many geographers that were hired on by retail companies to perform business functions. This coupled with a quantitative explosion helped produce a new era in real estate site selection (Kates, 1997).

Geographers working in the retail industry, known as marketing geographers, started looking at the retail environment in new ways. Quantitative and qualitative models were produced to better describe consumer actions and store locations. One of the earliest methods for real estate site selection is the Checklist Method (Nelson, 1958). This method uses a standardized list of principles to rank order current and potential sites. This method is more qualitative, but it does show an important step towards providing thought and order in the site selection process.

Applebaum (1966) provided the next significant model to be used in the real estate site selection process: The Analogue Model. This model uses analogous sites to help determine if a potential site will do well in a given market. After finding a sufficient number of analogous sites based upon location, demographics, and/or other factors that will possibly affect sales; a benchmark is developed to describe the potential site. This method is still used today and will be described in-depth later within this project.

Spatial-interaction (or gravity) models were also introduced in this period. These models provided more advanced quantitative methods for describing the trade area based on consumer actions and available real estate. Huff (1964) can be attributed to the advent of spatial-interaction modeling and the application to real estate site selection. He looked at how consumers visited different shopping areas and suggested that the "utility of a store depended on the size of the shopping center, travel time, and a parameter that

reflects the effect of travel time on various kinds of shopping trips" (Kates, 1997). This model will also be examined further within this project.

c. *GIS-based Analysis (1985-present)*

The Quantitative Analysis period provided many methods for modeling consumer behavior; however there was not a way to incorporate many of these applications into a centralized tool until the advent of computers in the workplace. As computers became more available and computing speeds increased, the methods and models that had been previous developed could be more readily applied in real estate site selection. GIS systems took these models and allowed analysts to apply them to real estate site selection quickly and easily.

GIS systems consist of computer hardware, software, and other peripherals that can transform spatially-referenced information into visually useful outputs that can be manipulated as needed (Castle, 1993). Castle points out that the main advantages of using GIS systems include:

- Data acquisition, input, and editing;
- Database management;
- Query and retrieval;
- Data analysis, modeling, synthesis; and
- Display, output, and dissemination of data and information.

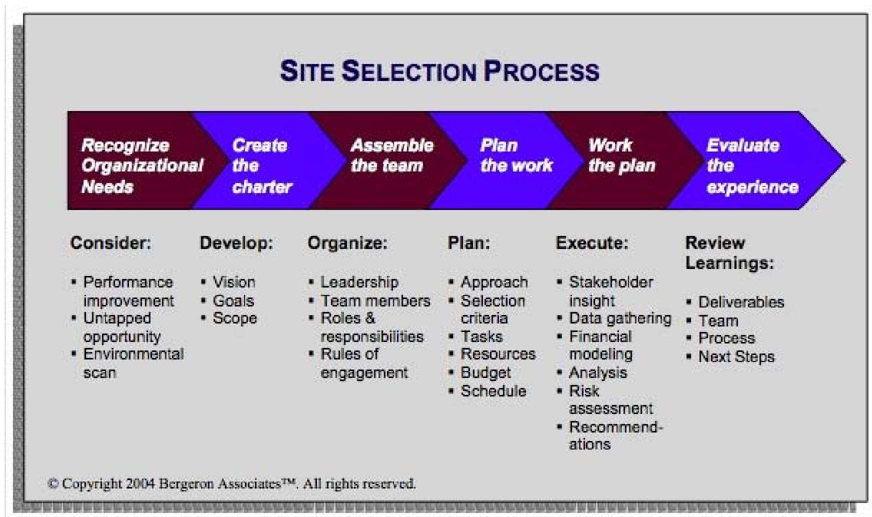
Now analysts could incorporate data and information from multiple sources quicker than previously available. Less dependence on qualitative and artistic type models was required for real estate site selection.

2. Real Estate Site Selection Process

As previously shown, the real estate site selection process has evolved over the past few decades. John Dawson, chief development officer for Dunkin' Brands, states that "Years ago, guys like myself did this on gut feelings" (Chittum, 2005). Site selection used to be a best-guess kind of a game. However recent technological advances, specifically in GIS software, have allowed companies and real estate executives to assemble data more easily in order to make informed decisions (Chittum, 2005).

Bergeron (2005) provides a model for the site selection process. Figure 1 shows this process from recognition of company needs to the ultimate deliverables. This

establishes a framework to understand the thought process of evolving real estate site selection techniques. For the purpose of this project, "Plan the Work" and "Work the Plan" will be looked at in greater detail (Bergeron, 2005). The operational site selection techniques to be discussed fall into these categories.



Source: Carol Bergeron's *Making site selection decisions in the worldwide economy* in The Handbook of Business Strategy, 2005.

Figure 1. Site Selection Process

Real estate site selection techniques can be divided into four main methods: the checklist method, analog method, regression modeling, and spatial interaction (gravity) modeling. All four methods have strengths and weaknesses and can be seen in industry today. The checklist method uses a checklist of factors (O'Malley et al., 1995). These factors generally managed without computer programs and provide a more artistic approach to site selection due to human interaction in the process. The analog method bases projections and comparison on similar stores, while regression modeling utilizes advanced computer models (O'Malley et al., 1995). Lee and Pace (2005) describe gravity modeling as "spatial dependencies among both consumers and retailers. The results show that both forms of spatial dependence exert statistically and economically significant impacts on the estimates of parameters" from the model.

3. Industries Affected

Multiple industries can be affected by improved real estate site selection techniques. Fryrear, Prill, and Worzala (2001) showed that the following industries were utilizing geographic information to enhance their real estate site selections:

- Retail
- Real estate development
- Government
- Property management
- Professional management
- Public utilities
- Warehousing, distribution
- Mini-storage
- Healthcare
- Banking

Of these industries, retail was the predominant industry shown to utilize geographic data for site selection (Fryrear et al., 2001). Other industries can also benefit from site selection techniques. The restaurant industry, specifically chain restaurants, tends to take a scientific approach when scouting prospective locations (Perlik, 2004). Also, service industry companies like quick-lube car centers can rely on basic factors to increase their chances for success. Educational institutions have even utilized site selection techniques when selecting new campuses (Alt, 1967). Three specific factors that these companies look at are "proximity of both residential and work areas, consumers who have discretionary income, and the presence of a 'retail cluster'" (Bennett, 2003).

As more companies within an industry enter the market, competition increases. Improved location can help optimize the success of a location and deter from opening suboptimal locations. Muller and Inman (1994) show that the "challenge is to identify those factors that will yield the most accurate predictions. This is where geodemographics and geographic information system (GIS) software play a role." The basic principles of choosing an optimal site transcend many industries. There are no limits to the application of these principles. So long as a company wishes to open a store in an ideal location, a site selection process will be utilized. The specific process utilized will be discussed later in this project.

4. Company Interviews

Speaking to companies who are expanding and/or decreasing their business and locations was essential for the project. Understanding how companies in the aforementioned industries chose sites helped frame the issues associated with site selection. Companies in the restaurant, retail, and grocery industries were interviewed. Although many companies did not divulge corporate information for this project, the few that did partake provided a basis for understand current practices.

Almost all companies maintained a real estate division, department, or team. The ultimate decision authority usually came from a subjective manager. All but one of the companies utilized a form of modeling to assist in their site selection process. However, only two of the companies utilized optimization techniques. Artificial intelligent algorithms were only utilized in one of these instances.

C. OPTIMIZATION USING ARTIFICIAL INTELLIGENCE

Looking at a potential site in isolation does not provide real estate analysts information about the market as a whole. Interactions between sites need to be examined when looking at an entire market. Also, consumer actions need to be accounted for. This is why optimization is an important factor in real estate site selection.

Optimizing utilizing genetic algorithms for real estate site selection is a relatively new concept. Genetic algorithms first became a viable option in search strategies due to the work of Holland in 1975 at the University of Michigan. He was the first person to apply the concepts of biological evolution into computational algorithms using the binary coding digits of 0 and 1. Holland was able to imitate the evolutional process of natural selection within a search system by using multiple artificially generated encoding and selection strategies. This was the first time that an artificially intelligent optimization technique was used in theory (Kim, 2001). The procedures for encoding genetic algorithms will be discussed in further detail later this project.

Genetic algorithms have been used since their development in many applications throughout the years. However, Goodchild's application of genetic algorithms to

location-allocation problems in 1986 marked the first time this form of optimization was used in a real-estate setting (Kim, 2001). Unfortunately he was unable to show that genetic algorithms were an improved form of optimization. He hypothesized that the role of supercomputer technologies would enable genetic algorithms to be the optimal optimization technique in the future (Hosage and Goodchild, 1986).

As time progressed genetic algorithms as a viable form of optimization continued to be researched. Densham (1991) continued Goodchild's research by trying to implement strategies for solving large location-based problems using genetic algorithms. He was ultimately able to show that by pre-processing data, genetic algorithms could be used as a good optimization technique. However, even by pre-processing data, the time needed to analyze data was unrealistic. The trade-off for improved results utilizing genetic algorithms was not necessarily worth the added time to get the results.

In the late 1990's great improvements were made in computing speeds. At this time the cost for higher computing power also came down. It was now more affordable to purchase the computing power necessary to analyze large location-based problems using genetic algorithms. Hurley, Moutinho, and Stephens (1995) along with Houck, Joines, and Kay (1996) showed improvements while using genetic algorithms. The location-allocation problem was now being optimized using these techniques. This problem dealt with the optimization of goods at specific locations. For example, if a company wanted to optimize its products throughout its existing stores, this would be a useful tool. This marked the first time genetic algorithms were effectively being utilized.

This project deals with utilizing genetic algorithms for real estate site selection. Optimizing consumer behavior and available real estate locations is a new concept for the application of genetic algorithms. Felicity George (1994) does provide an example of how genetic algorithms helped optimize car dealerships in England. Her results showed the advantage of genetic algorithms for optimization specifically for larger inputs. The idea of using this form of optimization in retail settings is not widely documented. The real estate site selection problem is also more complex than the location-allocation problem. It could be next step in the evolution of using genetic algorithms in industry for optimization.

D. CHAPTER SUMMARY

This chapter provided background information to lay the foundation for the issues raised throughout the remainder of this project. With respect to the broad issue of real estate site selection, it was shown to be a highly complex matter. As the issue was explored it was seen to be an area that is managed differently in various industries and companies within the private sector. A multitude of factors affect the idealized outcomes that a company may be seeking. Such a mix of factors requires careful examination and optimization in order to achieve the desired effects. The use of artificial intelligent algorithms to manage factors and optimize results in site selection is prime solution. Due to the decreasing cost of computing and increased knowledge of artificial intelligence in GIS, these artificial intelligent algorithms can minimize negative site selection for companies.

THIS PAGE INTENTIONALLY LEFT BLANK

III. REAL ESTATE SITE SELECTION ANALYSIS

A. INTRODUCTION

> Over the past decade, corporate real estate management has undergone a dramatic change as it has matured into a distinct discipline. As a part of the maturing process, the discipline has moved beyond its focus on basic real estate services. (Rabianski, DeLisle & Carn, 2001).

Rabianski et al. (2001) discuss how choosing an optimal site for a store or company is emerging into a complex field of study. Companies are no longer utilizing sites of opportunity and instinct to choose new sites. Instead, companies are relying on more scientific means of site selection.

In the retail industry, retailers are "paying greater attention to making sure that their stores are in the right places at the right times" (Buss, 2002). In order to make this happen, the real estate market needs to be analyzed. However, the analysis must not stop at that point. A more in-depth process needs to be utilized to ensure optimized results.

B. REAL ESTATE SITE SELECTION PROCESS

Bergeron (2005) provided a site selection process in Figure 1 (as seen in the previous chapter) detailing steps needed for optimal site selection. This project will focus on the "Plan the Work" and "Work the Plan" sections of this process. If a company desires to expand in a market or optimize its profit, site selection may need to be examined to open or close stores.

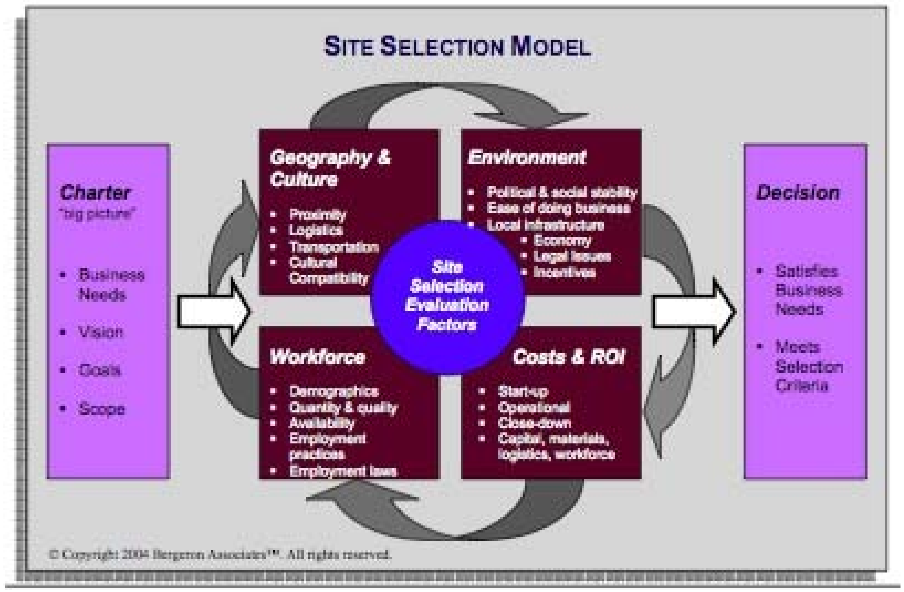
Many companies recognize their organization needs to choose potential sites carefully in order to allow for maximum profit. This falls into Bergeron's initial step of "Recognize Organizational Needs." If a company wants to expand its business, it must recognize what is needed in order to expand. Locating new areas for expansion is an example of one of these needs. Many times this includes expanding store or branch locations.

Her next step, “Create the Charter,” shows that the company will operate under a centralized vision or scope. This means that site selection for potential locations should fall in line with the company’s goals and mission. If the company’s vision were to become the top widget seller in the northeast, it would not make sense to look for new locations in the far west.

Bergeron’s next step outlined is “Assemble the Team.” Generally a company will have a real estate department or team that will analyze potential sites. They will assist management in making informed decisions prior to expanding in untapped markets or reassessing underperforming markets. Depending on the available talent and goals of the company, different teams may be assembled. Larger companies may have the availability to assemble a large department that is capable of conducting more advanced methods of site selection. This leads into her next step of “Plan the Work.”

Planning the work that needs to be done for real estate site selection can depend on the scope of the vision and the process to be utilized. A company that wants to grow nationally will most likely be examining trade areas across the country. However, smaller companies may be concentrating on regionalized growth. Either way, the process for site selection may be the same. Company real estate departments, and the analysts that work in them, must plan ahead for the process to be utilized. Four processes for site selection will be discussed in detail within this chapter.

Bergeron (2005) also provides a site selection model in Figure 2 showing the factors that need to be evaluated within the process. Four key factors are shown that need to be managed in order to ultimately provide a decision that either “satisfies business needs” or “meets selection criteria”: Geography & Culture, Environment, Costs & ROI, and Workforce.



Source: Carol Bergeron's *Making site selection decisions in the worldwide economy* in The Handbook of Business Strategy, 2005.

Figure 2. Site Selection Model

Geography and culture deal with the scope of the company's planned growth. As stated earlier, a company may only wish to grow locally. It would not want to be looking into national markets in areas that do not coincide with the company's goals and vision. Also, cultural factors may influence the company's decisions. Many companies provide products or services that do not fit in all cultures. A bank that provides services primarily to military members may find that its company culture does better located near military installations. Opening a branch in an area without a large military presence would not necessarily be the best business decision.

Environmental factors come from the area that the company wishes to expand. If the local economy of a trade area is currently in a recession, site expansion in that area may not be the best choice. Also, if there stores within a trade area are underperforming due to environmental factors such as politics or legal issues, the company might want to examine the potential implications of closing stores.

Costs and ROI (Return on Investment) can directly impact the decision to open or close stores in a market. The environment of a specific trade area can also drive them. Opening stores requires money to help that store open. Construction, new product, and

workforce costs can dictate whether or not it makes sense to open in a new market. The environment can impact these as well. Labor costs in New York City are higher than those in Houston, TX. These costs may drive new store size and product placement as well.

The final group of factors that Bergeron discusses is workforce related. The workforce available in a specific area may not consist of the desired quality. This workforce also may demand higher salaries as compared to other locations depending on the environment. Labor can cause its own problems when looking at the real estate site selection process. A site may be evaluated as high potential for sales from a consumer standpoint, however workforce may dictate otherwise with employment legalities and issues. An example of this could be a situation where a retail company would like to open stores in an urban area such as San Francisco or New York City. These two cities traditionally have extremely high costs of living. The retail company may not be willing to pay its potential employees higher wages to match standard rates in the city. This would cause potential problems for the company.

Managing these four factors can be a mentally taxing task. Companies must look at how they wish to manage these factors prior to conducting analysis. Generally data is collected into databases in order to be analyzed by corporate real estate departments. Buckner (1998) states "the information that is used in developing a database (and from what source it is derived) is a function of how quickly a decision needs to be made, the level of accuracy required, as well as developmental cost considerations." For example, a short-term decision could be desired on whether or not to open a retail site in a new trade area. Time may not allow for the acquisition of all necessary data and for a comprehensive analysis. Instead, the real estate team may decide to run a less comprehensive analysis. Current analysis techniques can range from a gut-instinct decision to highly complex algorithms. The company must establish their site selection techniques early in the site selection process prior acquiring data. Four main site selections techniques will be discussed in the following sections.

C. REAL ESTATE SITE SELECTION TECHNIQUES

As previously mentioned, multiple factors are managed within the real estate site selection process. In order to manage these factors, modern standard site selection techniques are utilized in theory and practice. O'Malley et al. (1995) provides a preliminary discussion on site selection techniques. They outline the checklist method, analog method, and regression modeling. These techniques currently are being utilized, however another selection technique has emerged from the work of Professor David Huff in the 1960's: spatial interaction modeling, sometimes referred to as gravity modeling. Figure 3 displays the various techniques utilized for real estate site selection.

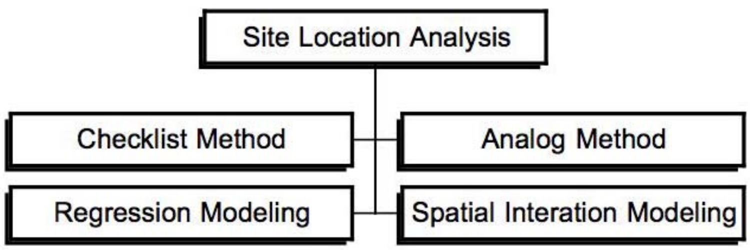


Figure 3. Site Selection Approaches

Although there are multiple methods for site location analysis, none of the methods are able to optimize multiple locations within a market to provide maximum profit. In order to provide optimized ROI, further optimization techniques need to be utilized. These will be discussed in Chapter IV. In order to gain a full understanding of current site location methods utilized in practice, all methods will be discussed in this chapter. However, the analog method and regression modeling will be studied further for optimization purposes.

1. The Checklist Method

The Checklist method utilizes a basic approach to site selection. Geodemographics, combined from both geographic and demographic information on populations, are treated as checklist of factors (O'Malley et al., 1995). The analyst simply checks off the information from a specific site. The more checks a specific site

gains; the more likely the site satisfies initial search criteria. Being that this method solely lists out parameters, quantitative results are not easily shown. Optimization of site selection criteria is not available.

Lilien and Kotler (1983) provide a useful example of this method by utilizing eight major site parameters. Each of these parameters is then subdivided into several attributes. Analysts check each parameter separately for the specified location and develop a list of strengths and weaknesses of all locations. The list compares all the locations using empirical rules and weights (Sulek, Lind, & Maruchek, 1995). This was considered a simple rule-based method that was inexpensive and quickly performed, however this was also highly subjective and possibly over-simplistic.

The checklist approach can be useful when looking at factors such as competition and consumer spending, demographic composition, and the comparison of potential real estate sites. An analyst will judge these factors next to each other. However, there is a great deal of judgment placed on these factors. This can be a good evaluation so long as the analyst is properly trained in this field.

The goal of this project is to ultimately identify a means of optimization for real estate site selection in a given market. The checklist method relies on a more artistic means of site selection analysis. A sample outcome of this approach is seen in Table 1. This checklist allows an analyst to verify specific attributes about a location. If the analyst was looking for a site that had a population under 25,000, a median household income greater than $40,000, and over 15% college graduates they would not be able to find all attributes based on this checklist. However, site 4 does have all but one of these attributes. Site 4 does not have the minimum population but as listed as a potential site. It had enough of the attributes in the checklist to be included as a potential site. The checklist method is a means for organizing this information in a database.

Sample Checklist					
Site #	Driving Distance >2	1997 Population >25,000	Median Household Income >$40,000	% College Graduate >15%	Possible Site Location?
1	No	Yes	No	No	No
2	Yes	Yes	No	Yes	Yes
3	Yes	Yes	No	No	No
4	Yes	No	Yes	Yes	Yes
5	Yes	Yes	Yes	No	Yes
6	Yes	Yes	No	No	No
7	Yes	No	No	No	No

Table 1. Sample Checklist for a Retail Store

The possible site locations are chosen based on a series of yes/no questions. This method can include some subjectivity depending on the questions being utilized. Due to the possible subjectivity of this method, it is not suitable for further analysis. Optimization of an entire market based upon subjective questions will not be possible as shown in Chapter IV. Artificial intelligent algorithms will need an actual model output. The following three methods (Analog, Regression, and Spatial Interaction) will be able to provide sufficient data to be used for optimization.

2. The Analog Method

The Analog Method assesses new sites by "identifying existing sites whose trade area and general attributes (and hence, revenues) resemble that expected for a new location" (Daniel, 1994). These can be done based on the same company's stores or its competitors. Analog modeling is the easiest modeling to understand due to the fact that analysts look at existing data in a specific trade area. A company can see what is already happening vice estimating a projection.

Mendes and Themido (2004) explain that the analog method is a "natural outcome" from the checklist method. This method attempts to gain objectivity. Analogous locations are grouped together by similar attributes as "empirical benchmarks." These attributes could be driving distance, population, or percentage of college graduates in the location area. Each location is then evaluated within the group. The new site's location-related parameters are evaluated on a pre-assigned scale. The analyst for each situation would determine the scale. Store sorting lists are then compiled to rate the existing stores against the potentially new store.

This method of real estate site selection is predominantly utilized in the retail industry; however the analog method tends to work across the entire spectrum of industries looking to expand their stores or branches. Also, the analog method of modeling site selection has the longest proven track record (Buckner, 1998). Due to the fact that analogs require very little mathematical computation as compared to regression and spatial interaction modeling, the use of the analog method may be utilized more readily with fewer resources available.

In order to conduct a site selection analysis utilizing the analog method, specific information needs to be available to the analyst. Generally this information comes from the company's own store point-of-sale (POS) data, competitors' data, census data, and other publicly available data. The analyst will generally dissect the trade area into sub-areas that will be analyzed as potential analogous areas for a new site. Zip codes are a common form of this sub-area grouping. Sales are then estimated for each sub-area on an annual or weekly basis as determined by the company. The capture rate for each sub-area is then calculated by dividing sales for that area by total sales. Table 2 provides an example of an analog table for a retail store in a sample study area. Note that the geographic areas are divided into zip codes. Total sales for the analog are $3,000,000. The capture rates for the zip codes only amount to 74.9%. This means that 25.1% of the sales come from outside of this trade area. The information provided by this analog table can then be used as inputs for financial models. The output from the analog is designed as a decision aide that needs to be analyzed in comparison to similar locations.

Trade Area Analog Table

Zip Code	Zip Name	Driving Distance	1997 Population	Median Household Income	% College Graduate	Capture Rate	Sales	Per Capita Sales
48141	Inkster	1.2	28,839	$ 27,905	8.9%	14.7%	$ 441,000	$ 15.29
48124	Dearborn	2.2	27,224	$ 39,042	19.6%	20.5%	$ 615,000	$ 22.59
48125	Dearborn Heights	2.6	20,862	$ 35,024	6.5%	5.5%	$ 165,000	$ 7.91
48128	Dearborn	2.8	18,728	$ 44,350	28.1%	22.5%	$ 675,000	$ 36.04
48127	Dearborn Heights	4.3	30,274	$ 41,965	14.7%	5.7%	$ 171,000	$ 5.65
48135	Garden City	4.5	27,239	$ 37,241	9.2%	3.5%	$ 105,000	$ 3.85
48184	Wayne	5.0	19,303	$ 33,002	7.9%	2.5%	$ 75,000	$ 3.89
	Trade Area Totals:		172,469	36,933	13.6%	74.9%	$ 2,247,000	$ 13.60
	Sales from Beyond Trade Area:					25.1%	$ 753,000	
	Grand Total:					100.0%	$ 3,000,000	

Table 2. Sample Analog Table for a Retail Store (Buckner, 1998)

Disadvantages of using analogs can be seen when inexperienced analysts manipulate data and insufficient data is utilized. The analog method can also be subjective. If an inexperienced analyst fails to ask specific questions while validating the results, the results could be invalid. The analyst needs to verify that the average trade area penetration levels projected for a specific market coincides with actual average trade area penetration levels seen in the parent databases. The analyst might also want to use reality-check questions such as "Does this make sense based on the database?"

The second potential disadvantage of the analog method comes from the database itself. If the company does not have sufficient data available, the analogs may not provide useful results. The results in the table above could easily mislead an analyst if insufficient data was collected. Sales for the trade area are stated at $3,000,000. If sales from beyond the trade area had not been accounted for, total sales would only have been $2,247,000. This could lead to incorrect per capita sales. Decisions may be made of these figures that would be incorrect. Collecting the right amount of data for the method of analysis can decide whether the analysis will lead to realistic results.

Overall the analog method provides the analyst a means to obtain proposed site sales forecasts from a historical reference of similar existing stores. Additional site selection techniques, such as regression and spatial interaction modeling, will go into further depth mathematically and can potentially provide more in-depth results

3. Regression Modeling

Regression Modeling employs "statistical analysis to derive linear or non-linear relationships between site attributes and site performance" (Daniel, 1994). Parameters such as distance, competition, and population are measured from existing store locations. These existing locations are analogous to potential new locations. This data is then used to calibrate a linear statistical equation (Mendes et al., 2004).

This form of modeling is widely used; however it is often misused—especially in all areas of the retail industry (Kotler, 1984). The large amount of data needed to feed the equations directly affects the quality of the output of the regression model. In order to ensure a quality output, the analyst needs to obtain many observations. Usually

companies with large point of sales (POS) observations can utilize these models more effectively. This provides complications for smaller and mid-sized companies from using regression modeling effectively in their real estate site selection methods. Many smaller and mid-sized companies may not have sufficient POS data in locations they wish to expand.

Multiple regression modeling provides a "means to model how a variable to be predicted varies with a set of independent predictors. Thus, the sales of a retail store from a specific ZIP Code may be related to distance from the store and the population of that ZIP Code" (Buckner, 1998). To further understand the mechanics of regression modeling, the actual statistical method should be analyzed. The following is an example of a multiple regression equation that can help forecast sales at any location:

$$\textit{Estimated Sales} = a + b_1x_1 + b_2x_2 + b_3x_3$$

a represents the intercept value or constant

x_1 represents distance as it relates to sales

x_2 represents population as it relates to sales

x_3 represents competition as it relates to sales and

b_1, b_2, and b_3 represent the multiplicative weighting assigned by regression to each variable (Buckner, 1998)

For this equation, the analyst would be evaluating estimated sales (the dependant variable) for a potential location. The estimated sales are dependent on the variables on the right side of the equation. This is the value being sought. The variables on the right side of the equation are considered independent variables (x_1, x_2, x_3). The independent variables will be shown to predict the value for estimated sales.

Although this method of site selection seems quite straightforward, there are many traps analysts should avoid. Regression modeling requires many assumptions that are not necessarily followed in the real world. Linear regression takes data and applies a straight-line to approximate the data points as described by the regression equation. This also assumes that the straight line is the best representation of the data. A linear

relationship may not represent the data appropriately. A curvilinear projection may work better. In this case, the independent variables would need to be transformed in order to work in a linear regression model. Again, this is a potential pitfall analysts need to be aware of while modeling.

Another potential problem is the independence of the independent variables. The independent variables should be mutually exclusive and not be related to each other. High income and high education both can be considered factors in bookstore sales, however they cannot be thought of as independent in contribution to sales. These interrelations in the data should be avoided in order to gain better results.

One final caution about regression models comes from graphing results. The results of a multiple regression model, as discussed above, will not truly fit into a line. A line would only be accurate for a regression using one independent variable. A two independent variable model would describe a plane. For multiple regressions, increasingly more difficult geometries would be represented. Because of this, simply stating that a regression line represents performance alone should indicate caution.

Advantages of regression modeling include its ability to make sense of complicated situations, specifically at the disaggregate level (trade area level). This means that a multiple regression model would be able to sort out classes of competition such as direct versus indirect. Regression models do a better job at predicting stores that are similar to those supported with data as opposed to new concept stores.

4. Spatial Interaction Modeling

Professor David Huff is considered the father of Spatial Interaction Modeling. His research in the 1960's pioneered this concept in site selection. Spatial interaction can be a powerful tool but is underutilized practice due to complexities, experience required, and information needed. Companies are able to assess sales by evaluating the situation from the consumer's perspective (Daniel, 1994). Furthermore, utilizing spatial statistics has been shown to provide "more realistic interference, better prediction, and more efficient parameter selection" (Pace, Barry, & Sirmans, 1998).

Newton's Law of Gravity states "two bodies are attracted to each other in proportion to their mass, and in inverse proportion to the square of the distance between then" (Buckner, 1998). This law holds true for spatial interaction models as well. William J. Reilly studied retail concentrations in cities throughout the United States in the early part of the 20th Century. He realized that there was a gravitational pull among customers and was able to model it into "Reilly's Law of Retail Gravitation." He stated that retail attraction is directly proportional to the size of two trading areas and indirectly proportional to the square of the distance between the two retail trading centers (Nelson, 1958). This can be seen as follows:

$$D_{A-B} = \frac{d}{1 + \sqrt{P_B / P_A}}$$

in which:

d = the distance, in miles, on major roads, between two adjacent towns, A and B.

PA = the population of Town A.

PB = the population of Town B.

DA-B = the edge, or boundary of, Town A's trading area, expressed in miles, toward Town B from the center of Town A.

Reilly's model takes into account both distance and the attractiveness of other shopping opportunities. It is based on the idea that agglomeration increases the attractiveness of stores, and that high-density areas represent agglomeration. In other words, shopping in higher density areas is considered more attractive. Reilly's law of retail gravitation was the first to quantify this idea for consumers in a retail setting based on Newton's law of planetary attraction. The decision between the cost of travel and the attractiveness of alternate shopping opportunities is the heart of this model. Today's spatial interaction models are based on the concepts introduced by O'Reilly's gravitation model (Brubaker, 2004).

a. Variables

Five main variables need to be adjusted by analysts when dealing with spatial interaction models. The analyst will alter one or more of these variables in order to simulate the trade area or market being studied more accurately (Buckner, 1998). Eventually the model is brought into a balanced state. There are many other variables that can be accounted for in the spatial interaction models. However the following lists the five main variables.

1) Draw accounts for the percentage of each of the competitors sales for a given trade area. A competitor may have a site that is situated on the outside of the designated trade area. This would provide a small draw. However, if the competitors store was located in the center of the trade area, they could have a higher draw. The analyst would need to estimate the draw in the initial planning stages of model development.

2) Curve provides an indication of the manner by which the store's sales are distributed. High curve would denote that more sales come from customers who live close to the location. A low curve number would show the opposite—a high proportion of sales come from customers living outside the trade area. Typically a smaller "mom and pop" store would have an extremely high curve as opposed to a major chain store like Wal-Mart. Major chains tend to pull in customers from greater distances as opposed to "mom and pop" stores (Buckner, 1998).

3) The density radius indicates the geographic extent of a given store's trade area showing the number of people that are living within a given distance of the site. A typical number for density radius is 2 miles. This would mean that each store in the model would pull customers from a 2 mile radius. This may or may not be appropriate for every model. The analyst needs to take caution when modeling this variable.

4) Leakage accounts for the potential sales dollars in a trade area that are being modeled but not absorbed by one of the stores in the model. The most common forms of leakage are the smaller, independent stores in a trade area. These stores are not easily accounted for in spatial interaction models. Since these models are

generally expensive to generate and complex to maintain, companies are usually more worried about competition from other regional or national chains.

5) Image is the final major variable in spatial interaction models. Image relates locations against each other. This is done through relative strength. The total of all images in a model should provide an average image rating of 100. A site with an image of 110 is considered better than average. Conversely, a site whose image is 70 is considered less desirable than average.

b. Strengths

Spatial interaction models provide multiple strengths. Specifically these models do not require the development of a store database. The analyst will generally work solely with population, demographics, and competitor's information. This can be good especially for companies that do not have a great deal of POS data or store databases. For companies that are relatively new to real estate site selection, this may be seen as great advantage.

Analysts have the ability, through spatial interaction models, to run "what-if" scenarios. Upon completion of a spatial interaction model for any given study area the analyst can then see how sales would affect potential and current stores while changing variables. This can be done for very large markets and trade areas. Instead of looking at a small interaction between two stores, a company would be able to assess sales interactions with a major metropolitan area. Through the "what-if" scenarios, real estate decisions could be evaluated based on a scientific method. However, the quality of the decision would rest on the quality of the model. Because of this reason, the limitation of spatial interaction models should be discussed.

c. Weaknesses

Spatial interaction models are essentially mathematical scenarios that try to mimic actual customer actions for a given trade area. If the model is not developed with sound reason and rigor, the quality of the model's output will be invalid. The analyst can not think of these models as solely gravity based. In order to truly gain the full power of spatial interaction, other variables other than size and distance must be introduced (Buckner, 1998). Specifically, experience is important while working on

these models. Experienced analysts typically can generate more realistic models based upon their experience in a given trade area.

The marketplace for all goods is ever-changing. New products and stores are introduced in attempt to gain a portion of a market. For example, specialty stores have opened competing with multiple types of competitors. Food/drug stores such as Longs, natural stores such as Whole Foods, and hypermarkets such as Wal-Mart all have overlap in some of their products. Some customers will drive 10 miles further to shop at a Wal-Mart when a Longs is one mile away from their house. Attempting to model this consumer desire can be difficult. Not all stores cater to the same consumer, yet they may have similar products. Understanding these differences is essential in producing a quality spatial interaction model.

Overall, spatial interaction models can be powerful tools for predicting consumer gravitation. Real estate site selection analysts need to be aware of all the strengths and weaknesses when using these models. If an analyst were to make an incorrect assumption, the results could be incorrect. Proper training and experience is necessary prior to working on these models. This is a key factor as to why many companies are not currently using these models within their real estate departments.

D. REAL ESTATE SITE SELECTION EXAMPLES

In order to gain a better understanding of how real estate site selection is conducted in practice, a real-world example is provided. As noted in the previous section, analog and regression models are the most widely utilized in practice and, therefore, will be shown in this example. The checklist method relies on too much subjectivity and is not able to be optimized for an entire market. The spatial interaction models are more accurate, however they require more stringent data requirements that may not readily available at most companies. The company shown in this example did not utilize spatial interaction modeling.

Analyzing the variables utilized in analog and regression models, along with their strengths and weaknesses, will allow a better differentiation between the methods. This

better understanding will also show when a certain method would be better to use than the other. Ultimately this will show how each method of site selection only analyzes specific locations within a market. It is always important to look at a single location within a market; however analyzing the entire market will provide insight in ways to optimize profit for the entire market vice a single location. This can only be done though advanced optimization techniques such as artificial intelligent algorithms (specifically genetic algorithms). The following example provides further insight into the predominately-utilized methods of real estate site selection.

> *The information for this example comes from a Fortune 500 retail company. The company and analyst shall remain anonymous throughout this project.*

1. The Scenario

A major retailer, who currently has stores of various sizes world-wide, was interested in maximizing profit in the Denver, Colorado area based on current and future site locations within the study area. In order to gain a better understanding of what mix of stores would be optimal for Denver, they utilized an outside source to assist in their market planning.

Figure 4 shows the company's existing trade area in Denver. The classifications of sites are noted in the legend. "Approved stores" are stores that are currently open and have been approved to stay open. "Hit list void" locations are sites that have been deemed deficient in the current market. This came from previous analysis of the trade area. These sites have specific properties associated with them. These could be malls, lifestyle centers, outlets, etc. "In/Out" sites are the locations to be analyzed within the site selection analysis. They are sites that can be either included in future planning by remaining open or excluded by closing the store. "Opt Void" stores are areas that have noted voids in the specific market from previous analysis. There are not specific site locations associated with these voids. They are only utilized to show areas of future growth potential. Finally the figure shows "Sacred Cows". These are stores that are performing well. They are not to be considered for any changes in the market planning process.

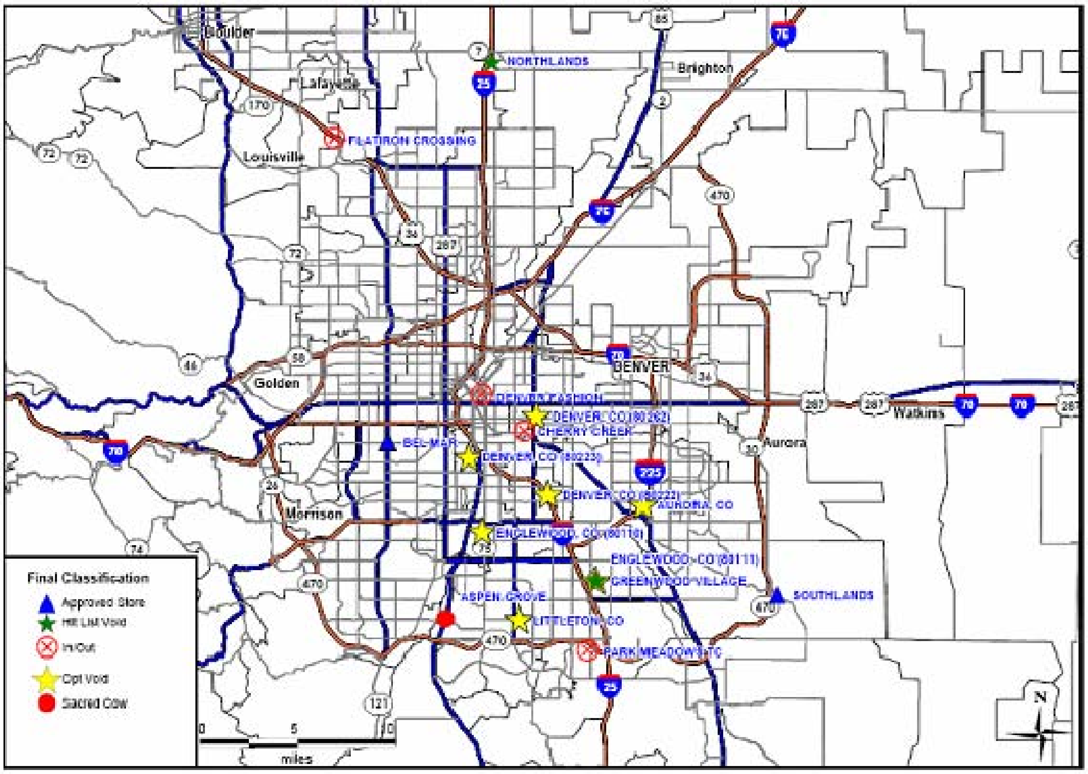


Figure 4. Denver trade area with current and potential store mix

The company wanted to look at their current mix of stores. They were interested in whether they should open new stores, close existing stores, or keep the current mix as-is. Keeping a store open was called "in." Closing a store was called "out." Before going into the market planning process, the company set guidelines to help them out. These guidelines included the following list of parameters:

- "Sacred Cows" should not be considered in the in/out process.
- Focus on "Hit list voids" when conducting market analysis.
- Internal Rate of Return (IRR) was utilized for a hurdle rate at a minimum of 25%.
- Net Present Value (NPV) of existing and potential stores was calculated using a lifespan of 15 years.

This list of guidelines helped the third-party analysts conduct market analysis for the Denver trade area.

2. The Process

The analysts developed a method to explore possible options in the Denver area. They were given guidelines (above) and had access to the company's current store database and POS information. This combined with population data provided sufficient information to develop a plan.

The analysts utilized the company's store databases, POS data, and population data to run 34 scenarios for the Denver market. A set of analogous stores were first pulled from the company's databases. These stores matched specified search criteria that mimicked a potential site's characteristics. One of the 34 scenarios is presented in this project. This scenario shows the process of opening a core format store in Northlands. Pearl Street in Boulder, Colorado is also closed in this scenario. Pearl Street is a large women's store in a street shopping location.

a. Use of Analogs

The main concept behind the use of analog modeling is that the sales of a proposed store will perform similarly to other stores that exist within a company. Analysts must choose these similar stores based on a set list of criteria. Ideally, an analyst would want only analogs that strongly match the proposed store's variables. This may not always be feasible. The following steps outline the general approach used by this company to choose analog sites. The analyst would start at step 1 and move towards step 4.

1. Restrict the search to match the location type, format of store, market, and range of density class.
2. If more matches are needed, relax the market constraint allowing market class or market class range within the same region.
3. Refine the search by range of trade area population.
4. Refine the search by range of effective population score and/or competition.

This list shows that the most important factors are location, format, market, and range of density class. However, these factors alone must not be the only input into the model. The location of the analog should be similar. This means that a rural analog should be used for a proposed rural store. The format must be similar also. A large style format

should not be used as an analog for a proposed smaller store. The same thought process should be used for the type of market (population profile, etc). Upon finalizing the analog set, the analyst should begin to compare essential information for the proposed site along with the analog stores.

Figure 5 shows the analog set for the proposed Northlands store. The analogs similar to the proposed store come from all over the United States. Stores included come from Knoxville, Syracuse, Sarasota, Fort Lauderdale, and other cities nowhere near Denver, CO. Within this analog sales forecast model two specific factors are evaluated closely: $/Eff Cap and Capture Rate. $/Eff Cap means the dollars spent per the effective capita. The total dollars spent in a given area are divided by the effective trade area population. The effective trade area population is calculated based upon a population index. The average index would be 1.0, however if the all the trade area households spent more than most the index would be greater than 1.0. This analog model only has one analog with a population index great than 1.0: Hartford, CT. Hartford's population index is 1.29. For this analog model, the $/Eff Cap was $5.21.

The Capture Rate shown in this analog model was 69.8%. In other words, 69.8% of the sales for this model came from within the trade area. This would mean that 30.2% of the sales came from outside the trade area for this analog model.

Thirty three other analog models were run for this trade area. The analog model presented here only shows the analogs for the site that was selected to open: Northlands. The analysts working on this scenario conducted the same procedures for the other alternatives within the trade area. Ultimately Northlands was chosen to open based upon the company's goals. The presented analog provided the optimal results out of the 34 analogs conducted. The capture rate and $/Eff Cap were higher for this analog model, but the decision was not based up on the analog model alone. The analysts also looked at regression models to help ascertain with the best scenarios would be. The following section will discuss how regression models were used in this scenario.

Aggregate - Analog Stores

Analyst:	USA\je49101	**Scenario:**	Scenario 7 - Base 3 Open 80038
Date:	9/30/2005	**Comments:**	Base 3 Open 80038
		Study Area:	Denver-Boulder MP - JPH
		Comments:	Created for BR MP scenarios 9/26/05 - JPH
Site ID:	5441		
Site Name:	Northlands		
Comments:			
Deal Type:	Open		
Store #:	55441		
Format:	CORE		
Location Type:	Mall		
Sq. Ft.:	8000		
Density Class:	Rural		
Market Index:	0.9		
City:	Broomfield	**Latitude:**	40.0008
State:	CO	**Longitude:**	-104.9800
Zip:	80038	**MI Center ID:**	N/A
Market ID:	3060		
MSA:	Greeley, CO		
Market Class:	Large		
Region:	Mountain		

Total

Store #	Store Name	MSA	Market Class	Density Class	Location Type	Mall / Fashion	Format	Total Size	$ / Sqft	Total Pop	Eff Pop	Eff Pop Index	Tot Pop / Sqmi	MHI	% HH Inc > $100K	% Bach / Grad	% Married HH No Kids	% White Collar	% Tot Pop Top 10 MV	% White Pop	SIS Index	$ / Tot Cap	$ / Eff Cap	Trade Area Sales	Beyond Sales	Total Sales	CHAID Factor	Capture Rate
3133	Parkway City Mall (Us E	Huntsville, AL	Small	Light Subur	Mall	B/3	CORE	7,000	$224	400,845	315,450	0.79	286	$48,621	16%	30%	30%	64%	34%	75%	0.0	$2.98	$3.78	$1,193,539	$374,896	$1,568,436	-28.0%	76.1%
8253	Woodland Mall - MI	Grand Rapids et al, MI	Mid/Small	Suburban	Mall	A/2	CORE	5,338	$423	524,281	385,430	0.74	876	$52,681	16%	27%	25%	60%	27%	81%	34.0	$2.90	$3.95	$1,522,415	$734,633	$2,257,048	-16.0%	67.5%
8109	Holyoke Mall	Springfield, MA	Small	Light Subur	Mall	A/2	CORE	3,699	$621	525,618	340,763	0.65	1,038	$44,989	13%	25%	25%	63%	20%	79%	0.0	$2.61	$4.03	$1,371,643	$927,040	$2,298,683	5.0%	59.7%
8538	South Hills Village (Us	Pittsburgh, PA	Mid/Large	Suburban	Mall	A/2	CORE	7,350	$326	383,014	347,239	0.91	1,159	$51,193	17%	31%	31%	70%	41%	94%	34.2	$4.18	$4.61	$1,599,085	$794,789	$2,393,875	11.0%	66.8%
8239	West Town Mall	Knoxville, TN	Mid/Small	Light Subur	Mall	+A/2	CORE	4,864	$479	453,166	336,687	0.74	648	$45,106	14%	28%	29%	65%	30%	90%	0.0	$3.43	$4.61	$1,553,274	$777,062	$2,330,336	-1.0%	66.7%
8448	Columbiana Center	Columbia, SC	Small	Exurban	Mall	A/2	CORE	6,505	$353	471,059	363,788	0.77	674	$48,936	15%	32%	26%	70%	34%	63%	0.0	$3.57	$4.63	$1,683,777	$611,835	$2,295,612	2.0%	73.3%
7683	Avon Marketplace (Us E	Hartford, CT	Mid/Small	Exurban	Lifestyle	-/0	CORE	7,013	$344	293,245	378,556	1.29	573	$67,101	27%	38%	31%	73%	50%	89%	40.8	$6.04	$4.68	$1,771,736	$644,203	$2,415,939	6.0%	73.3%
8094	Ft Lauderdale Gall	Fort Lauderdale, FL	Large	Light Urban	Mall	B/1	CORE	6,584	$401	444,743	395,705	0.89	4,399	$44,129	15%	24%	23%	61%	34%	65%	25.6	$4.21	$4.73	$1,870,533	$766,714	$2,637,247	-8.0%	70.9%
8283	Haywood Mall	Greenville et al, SC	Mid/Small	Light Subur	Mall	+A/2	CORE	5,513	$453	476,904	336,349	0.71	646	$47,138	15%	27%	29%	60%	29%	79%	0.0	$3.42	$4.85	$1,631,424	$867,974	$2,499,398	8.0%	65.3%
8428	Friendly Center	Greensboro et al, NC	Mid/Large	Suburban	Lifestyle	-/0	CORE	5,996	$507	560,946	424,704	0.76	532	$48,938	16%	29%	28%	63%	35%	68%	14.2	$3.99	$5.27	$2,236,911	$800,517	$3,037,428	23.0%	73.6%
8132	Hanes	Greensboro et al, NC	Mid/Large	Light Subur	Mall	A/2	CORE	6,701	$406	585,792	356,480	0.61	365	$47,167	13%	22%	31%	58%	21%	77%	23.6	$3.22	$5.30	$1,887,656	$834,844	$2,722,501	9.0%	69.3%
8295	Hamilton Place	Chattanooga, TN-GA	Small	Exurban	Mall	A/2	CORE	5,344	$395	567,074	305,079	0.54	389	$43,283	12%	19%	31%	56%	17%	82%	0.0	$2.87	$5.33	$1,626,664	$481,826	$2,108,490	5.0%	77.1%
7686	Fox River Mall (Us Br)	Appleton et al, WI	Small	Exurban	Mall	+A/2	CORE	7,042	$338	515,123	316,475	0.61	659	$52,798	14%	24%	28%	60%	21%	92%	0.0	$3.36	$5.47	$1,730,130	$650,722	$2,380,852	11.0%	72.7%
8598	Franklin Park (Us Br)	Toledo, OH	Small	Suburban	Mall	A/2	CORE	7,164	$366	512,148	333,107	0.65	1,441	$45,631	14%	22%	26%	58%	28%	79%	0.0	$3.59	$5.53	$1,840,655	$780,166	$2,620,821	-5.0%	70.2%
8168	Carousel Center	Syracuse, NY	Mid/Small	Light Urban	Mall	A/2	CORE	7,778	$451	425,912	333,058	0.78	866	$45,939	14%	29%	25%	68%	30%	83%	0.0	$4.35	$5.56	$1,851,049	$1,660,385	$3,511,434	-5.0%	52.7%
8437	Southgate Plaza	Sarasota et al, FL	Mid/Small	Suburban	Mall	A/1	CORE	5,275	$529	475,261	372,354	0.78	925	$48,594	16%	27%	38%	64%	20%	91%	0.0	$4.56	$5.82	$2,165,877	$623,577	$2,789,454	20.0%	77.6%
8485	Bayshore Mall	Milwaukee et al, WI	Mid/Large	Suburban	Mall	A/3	CORE	6,265	$458	358,458	343,611	0.96	2,141	$47,698	16%	31%	21%	66%	43%	53%	29.2	$5.87	$6.12	$2,103,255	$768,404	$2,871,660	-17.0%	73.2%
8268	Mall Of Louisiana	Baton Rouge, LA	Small	Light Subur	Mall	+A/2	CORE	5,436	$606	531,401	370,446	0.70	700	$45,243	14%	27%	25%	64%	32%	63%	0.0	$4.35	$6.24	$2,310,851	$983,183	$3,294,034	-3.0%	70.2%
8575	Smith Haven (Us Br)	Nassau et al, NY	Very Large	Light Subur	Mall	+A/2	CORE	8,000	$502	479,306	408,188	0.85	2,400	$76,575	33%	28%	32%	70%	28%	89%	0.0	$5.78	$6.78	$2,769,132	$1,243,833	$4,012,965	2.0%	69.0%
8545	Fayette Mall (Us Br)	Lexington, KY	Small	Suburban	Mall	+A/2	CORE	8,240	$387	402,316	328,465	0.82	385	$46,352	15%	31%	26%	64%	40%	85%	0.0	$5.60	$6.86	$2,252,062	$936,455	$3,188,517	11.0%	70.6%
Database Averages		Not entire database						6,355	$428	469,331	354,597	0.78	1,055	$49,906	16%	28%	28%	64%	31%	79%	10.1	$4.04	$5.21	$1,848,584	$813,153	$2,661,736	1.5%	69.8%

Figure 5. Analogs for Northlands site

b. Use of Regression

The real estate analysts utilized a regression model to help show sales forecasts for the proposed Northlands store. These regression models are considered simple because sales are only a function of distance. The company has many regression curves relating average sales per effective population to straight line distance from a given store. These curves are grouped together based upon store type. For example, there are a set of regression curves for mall type stores and another for lifestyle center stores. These curves are further subdivided into market type. A possible set of curves could be mall locations in medium markets (based upon the company's definition of a medium market).

Figure 6 shows four regression outputs for the proposed Northlands store below the analog model output. The four regressions are system isolation, analyst isolation, system sequential, and analyst sequential. The system outputs depict exactly what the regression curves dictate based upon the company's databases. The company utilizes store data, POS data, and census data to populate its databases. The analyst outputs take into account user knowledge. The analysts may have other knowledge of the area or the regressions and accounted for them in their adjusted regression output. The isolation or sequential outputs account for how the model was run. Regression models run in isolation assume the store is opening up without any other stores in surrounding areas. The sequential models assume that other stores are currently open or will be opening and will cannibalize some of this store's sales. In this example there was no difference between the isolated or sequential models.

Total

Store #	Store Name	MSA	Market Class	Density Class	Location Type	Mall / Fashion	Format	Total Size	$ / Sqft	Total Pop	Eff Pop	Eff Pop Index	Tot Pop / Sqmi	MHI	% HH Inc > $100K	% Bach / Grad	% Married HH No Kids	% White Collar	% Tot Pop Top 10 MV	% White Pop	SIS Index	$ / Tot Cap	$ / Eff Cap	Trade Area Sales	Beyond Sales	Total Sales	CHAID Factor	Capture Rate
3133	Parkway City Mall (Us E	Huntsville, AL	Small	Light Subur	Mall	B/3	CORE	7,000	$224	400,845	315,450	0.79	286	$48,621	16%	30%	30%	64%	34%	75%	0.0	$2.98	$3.78	$1,193,539	$374,896	$1,568,436	-28.0%	76.1%
8253	Woodland Mall - Mi	Grand Rapids et al, MI	Mid/Small	Suburban	Mall	A/2	CORE	5,338	$423	524,281	385,430	0.74	876	$52,681	16%	27%	25%	60%	27%	81%	34.0	$2.90	$3.95	$1,522,415	$734,633	$2,257,048	-16.0%	67.5%
8109	Holyoke Mall	Springfield, MA	Small	Light Subur	Mall	A/2	CORE	3,699	$621	525,618	340,763	0.65	1,038	$44,989	13%	25%	25%	63%	20%	79%	0.0	$2.61	$4.03	$1,371,643	$927,040	$2,298,683	5.0%	59.7%
8538	South Hills Village (Us	Pittsburgh, PA	Mid/Large	Suburban	Mall	A/2	CORE	7,350	$326	383,014	347,239	0.91	1,159	$51,193	17%	31%	31%	70%	41%	94%	34.2	$4.18	$4.61	$1,599,085	$794,789	$2,393,875	11.0%	66.8%
8239	West Town Mall	Knoxville, TN	Mid/Small	Light Subur	Mall	+A/2	CORE	4,864	$479	453,166	336,687	0.74	648	$45,106	14%	28%	29%	65%	30%	90%	0.0	$3.43	$4.61	$1,553,274	$777,062	$2,330,336	-1.0%	66.7%
8448	Columbiana Center	Columbia, SC	Small	Exurban	Mall	A/2	CORE	6,505	$353	471,059	363,788	0.77	674	$48,936	15%	32%	26%	70%	34%	63%	0.0	$3.57	$4.63	$1,683,777	$611,835	$2,295,612	2.0%	73.3%
7683	Avon Marketplace (Us E	Hartford, CT	Mid/Small	Exurban	Lifestyle	-/0	CORE	7,013	$344	293,245	378,556	1.29	573	$67,101	27%	38%	31%	73%	50%	89%	40.8	$6.04	$4.68	$1,771,736	$644,203	$2,415,939	6.0%	73.3%
8094	Ft Lauderdale Gall	Fort Lauderdale, FL	Large	Light Urban	Mall	B/1	CORE	6,584	$401	444,743	395,705	0.89	4,399	$44,129	15%	24%	23%	61%	34%	65%	25.6	$4.21	$4.73	$1,870,533	$766,714	$2,637,247	-8.0%	70.9%
8283	Haywood Mall	Greenville et al, SC	Mid/Small	Light Subur	Mall	+A/2	CORE	5,513	$453	476,904	336,349	0.71	646	$47,138	15%	27%	29%	60%	29%	79%	0.0	$3.42	$4.85	$1,631,424	$867,974	$2,499,398	8.0%	65.3%
8428	Friendly Center	Greensboro et al, NC	Mid/Large	Suburban	Lifestyle	-/0	CORE	5,996	$507	560,946	424,704	0.76	532	$48,938	16%	29%	28%	63%	35%	68%	14.2	$3.99	$5.27	$2,236,911	$800,517	$3,037,428	23.0%	73.6%
8132	Hanes	Greensboro et al, NC	Mid/Large	Light Subur	Mall	A/2	CORE	6,701	$406	585,792	356,480	0.61	365	$47,167	13%	22%	31%	58%	21%	77%	23.6	$3.22	$5.30	$1,887,656	$834,844	$2,722,501	9.0%	69.3%
8295	Hamilton Place	Chattanooga, TN-GA	Small	Exurban	Mall	A/2	CORE	5,344	$395	567,074	305,079	0.54	389	$43,283	12%	19%	31%	56%	17%	82%	0.0	$2.87	$5.33	$1,626,664	$481,826	$2,108,490	5.0%	77.1%
7686	Fox River Mall (Us Br)	Appleton et al, WI	Small	Exurban	Mall	+A/2	CORE	7,042	$338	515,123	316,475	0.61	659	$52,798	14%	24%	28%	60%	21%	92%	0.0	$3.36	$5.47	$1,730,130	$650,722	$2,380,852	11.0%	72.7%
8598	Franklin Park (Us Br)	Toledo, OH	Small	Suburban	Mall	A/2	CORE	7,164	$366	512,148	333,107	0.65	1,441	$45,631	14%	22%	26%	58%	28%	79%	0.0	$3.59	$5.53	$1,840,655	$780,166	$2,620,821	-5.0%	70.2%
8168	Carousel Center	Syracuse, NY	Mid/Small	Light Urban	Mall	A/2	CORE	7,778	$451	425,912	333,058	0.78	866	$45,939	14%	29%	25%	68%	30%	83%	0.0	$4.35	$5.56	$1,851,049	$1,660,385	$3,511,434	-5.0%	52.7%
8437	Southgate Plaza	Sarasota et al, FL	Mid/Small	Suburban	Mall	A/1	CORE	5,275	$529	475,261	372,354	0.78	925	$48,594	16%	27%	38%	64%	20%	91%	0.0	$4.56	$5.82	$2,165,877	$623,577	$2,789,454	20.0%	77.6%
8485	Bayshore Mall	Milwaukee et al, WI	Mid/Large	Suburban	Mall	A/3	CORE	6,265	$458	358,458	343,611	0.96	2,141	$47,698	16%	31%	21%	66%	43%	53%	29.2	$5.87	$6.12	$2,103,255	$768,404	$2,871,660	-17.0%	73.2%
8268	Mall Of Louisiana	Baton Rouge, LA	Small	Light Subur	Mall	+A/2	CORE	5,436	$606	531,401	370,446	0.70	700	$45,243	14%	27%	25%	64%	32%	63%	0.0	$4.35	$6.24	$2,310,851	$983,183	$3,294,034	-3.0%	70.2%
8575	Smith Haven (Us Br)	Nassau et al, NY	Very Large	Light Subur	Mall	+A/2	CORE	8,000	$502	479,306	408,188	0.85	2,400	$76,575	33%	28%	32%	70%	28%	89%	0.0	$5.78	$6.78	$2,769,132	$1,243,833	$4,012,965	2.0%	69.0%
8545	Fayette Mall (Us Br)	Lexington, KY	Small	Suburban	Mall	+A/2	CORE	8,240	$387	402,316	328,465	0.82	385	$46,352	15%	31%	26%	64%	40%	85%	0.0	$5.60	$6.86	$2,252,062	$936,455	$3,188,517	11.0%	70.6%
Database Averages		Not entire database						6,355	$428	469,331	354,597	0.78	1,055	$49,906	16%	28%	28%	64%	31%	79%	10.1	$4.04	$5.21	$1,848,584	$813,153	$2,661,736	1.5%	69.8%
Selected Site (System - Isolation)																												
55441	Northlands	Greeley, CO	Large	Rural	Mall		CORE	8,000	$137	475,224	363,166	0.76	671	$64,310	23%	28%	28%	64%	35%	83%	22.6	$4.60	$6.02	$798,295	$295,260	$1,093,555	0.0%	73.0%
Selected Site (Analyst - Isolation)																												
55441	Northlands	Greeley, CO	Large	Rural	Mall		CORE	8,000	$137	475,224	363,166	0.76	671	$64,310	23%	28%	28%	64%	35%	83%	22.6	$5.17	$6.76	$798,295	$429,851	$1,228,146	0.0%	65.0%
Selected Site (System - Sequential)																												
55441	Northlands	Greeley, CO	Large	Rural	Mall		CORE	8,000	$137	475,224	363,166	0.76	671	$64,310	23%	28%	28%	64%	35%	83%	22.6	$4.60	$6.02	$798,295	$295,260	$1,093,555	0.0%	73.0%
Selected Site (Analyst - Sequential)																												
55441	Northlands	Greeley, CO	Large	Rural	Mall		CORE	8,000	$137	475,224	363,166	0.76	671	$64,310	23%	28%	28%	64%	35%	83%	22.6	$5.17	$6.76	$798,295	$429,851	$1,228,146	0.0%	65.0%

Figure 6. Regression results for Northlands site

The regression model outputs show higher $/Eff Cap for both the system and analyst models. However, the system accounts for a 73% capture rate. The analyst shows a 65% capture rate. The analog's capture rate was 69.8%. Part of the reason for the analysts difference in $/Eff Cap and Capture Rate come from their adjustment of drive time (distance) and trade area. Figure 7 shows the system's automated trade area. The trade area is outlined in burgundy.

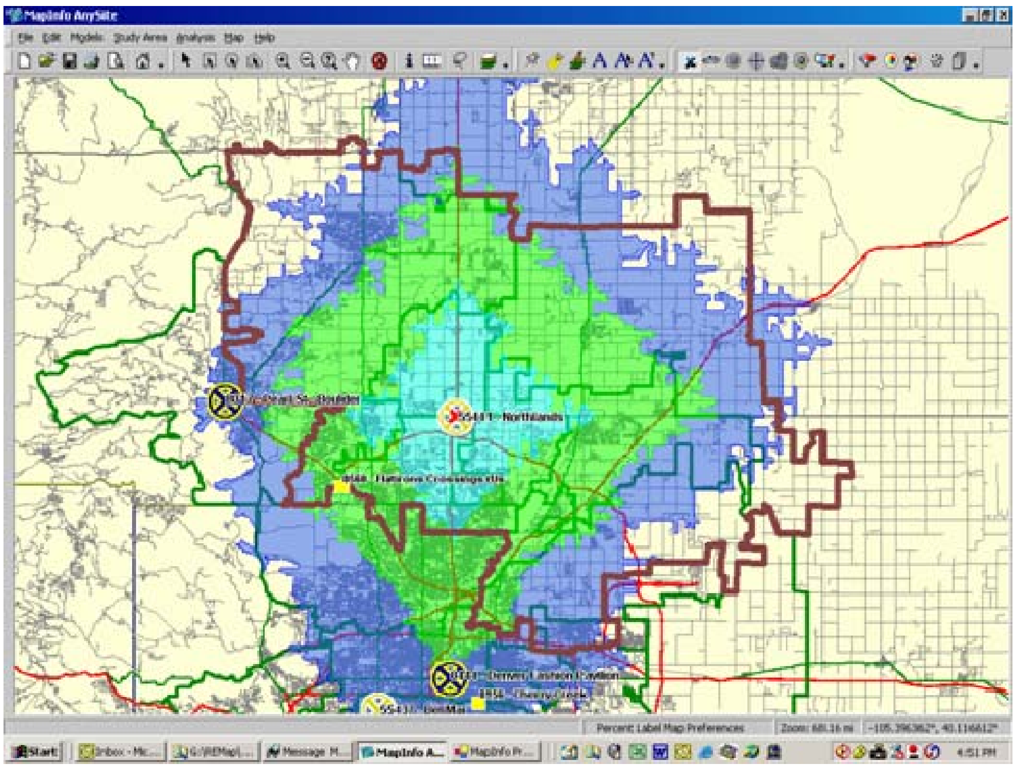


Figure 7. System Trade Area

Figure 8 shows the analysts adjusted trade area. The analysts felt that the proposed Northlands store would draw customers from the northern areas more so than the systems projection. The analyst adjusted the trade area to represent their assumptions. This can be seen below outlined in burgundy.

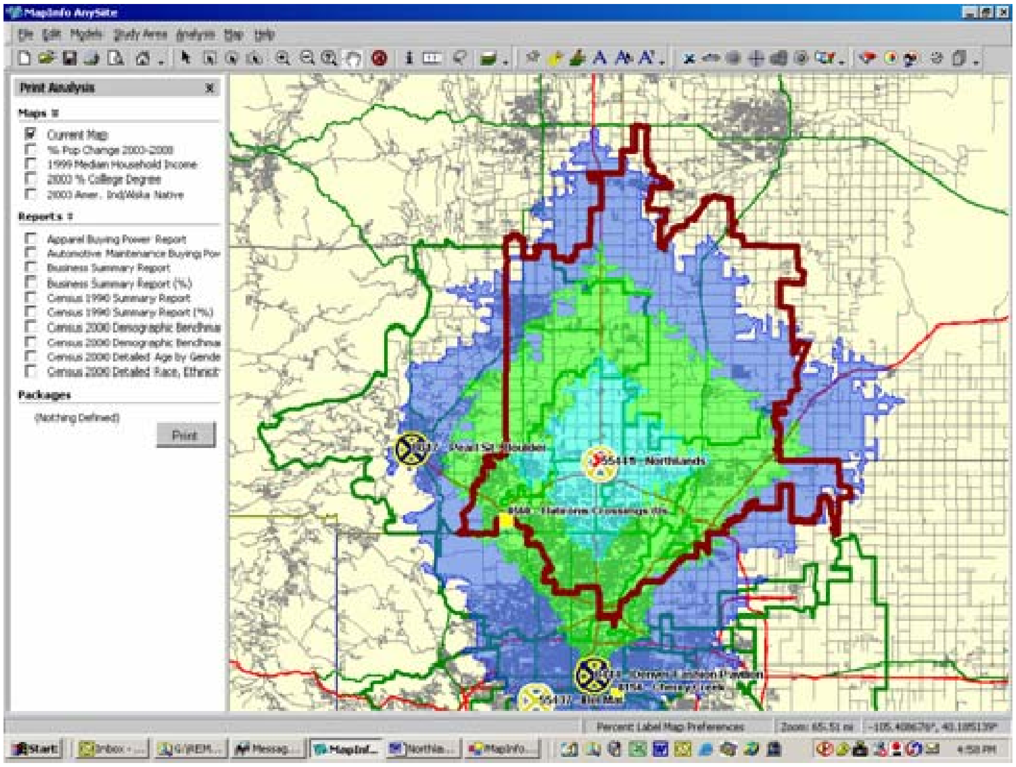


Figure 8. Analyst Adjusted Trade Area

After running analog and regression models for the proposed Northlands store, the analyst has a relatively good idea of how the proposed store will perform. This is all based upon the company's previously recorded historical data. There are other factors to assess prior to making an ultimate decision. Also, keep in mind that this same process was done for 33 other proposed locations.

c. Cannibalization / Recapture

Opening a new store at the Northlands location would potentially affect other stores in the trade area. The new store would cannibalize on the sales of current stores. This would decrease other sales while adding to the sales of the new store. This affect is referred to as cannibalization. The same can be said for the opposite process. If the company were to close a store, the surrounding stores in a given trade area may see a possible increase in sales due to recaptured customers. Customers would not have their usual store to shop at in the trade area. They would possibly go to another store in the trade area. This store would recapture this customer's sales for the company.

Figure 9, below, shows the impact of opening the Northlands store on the other stores in this market. For example, the Flatirons Crossings store, which is a full format mall store, would lose 6.5% of total sales based upon Northlands opening as shown in Figure 9. Referring to Denver trade area map above, this would potentially make sense. The Flatirons Crossings store is closest to the proposed Northlands store. The stores closest to the Northlands location should be cannibalized the most generally.

Store	Store Name	Action Type	Format	Location Type	Parent Scenario Sales System	Parent Scenario Sales Analyst	Cumulative Impacted Sales System	Cumulative Impacted Sales Analyst	Cumulative Compx System	Cumulative Compx Analyst
Existing Stores (No Closures / No Reconfigures)										
8560	Flatirons Crossings [Us		FULL	Mall	$4,733,584	$4,733,584	$4,423,328	$4,423,328	-6.5%	-6.5%
3047	Aspen Grove [Us BR]		CORE	Lifestyle	$2,004,520	$2,004,520	$1,991,217	$1,991,217	-0.7%	-0.7%
8156	Cherry Creek		CORE	Mall	$5,474,440	$5,474,440	$5,447,060	$5,447,060	-0.5%	-0.5%
55437	Bel Mar		CORE	Lifestyle	$2,703,739	$2,703,739	$2,697,671	$2,697,671	-0.2%	-0.2%
55438	Denver Fashion Pavilion		CORE	Lifestyle	$2,778,032	$2,778,032	$2,775,964	$2,775,964	-0.1%	-0.1%
8261	Park Meadows		FULL	Mall	$4,773,482	$4,773,482	$4,773,482	$4,773,482	0.0%	0.0%
55436	Southlands		CORE	Lifestyle	$2,611,879	$2,611,879	$2,611,879	$2,611,879	0.0%	0.0%
Subtotals:					$25,085,677	$25,085,677	$24,727,261	$24,727,261	-1.4%	-1.4%
Scenario Actions										
55445	Northlands	Open	CORE	Mall	$0	$0	$1,044,379	$1,044,379		
Subtotals:					$0	$0	$1,044,379	$1,044,379		
Total Market:										
					$25,085,677	$25,085,677	$25,771,640	$25,771,640	2.7%	2.7%
Net New:										
							$685,963	$685,963		

Figure 9. Northlands' cannibalization/recapture

3. The Results

The ultimate results of this scenario opened the Northlands store and closed the Pearl Street store. Figure 10 shows the Denver selection results. These results summarize the trade area based on the actions discussed here. Each store and void (potential site) is listed with a Year 0 sales, IRR (internal rate of return), and NPV (net present value). The baseline figures are for what the company currently has in existence for the study area. The recommend scenario figures show what the recommend scenario will provide. The final set of figures show the variance between the two. The scenario that was run that produced the highest NPV is also shown for comparison.

The results from this example are intended for use in the decision process. These are not financial models. As discussed earlier, these results may not be the optimal results for the study area. The scenario chosen as the best scenario does provide better results than the other proposed. It has a higher IRR at 31.9%. This is decrease in IRR from the baseline IRR of 33.0%, however the recommended scenario does have a higher

NPV of $1,511,052 over the baseline NPV. There is a tradeoff with this scenario. The scenario with the highest NPV has a smaller IRR of 30.1%. Each scenario must be looked at in comparison to the other. Even though the recommended scenario did not have the highest NPV, it was considered better than the scenario with the highest NPV.

Recommended Deployment

			BASELINE			RECOMMENDED: SCENARIO 11			VARIANCE			
Store/Voids	Location Name	Evaluated	Year 0 Sales	IRR	NPV	Year 0 Sales	IRR	NPV	Year 0 Sales	Year 0 Sales % Change	IRR (ppt change)	NPV
8017	PEARL ST - BOULDER	OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
8444	DENVER FASHION PAV	IN/OUT	2,402,517	23.4%	1,925,359	2,402,517	23.4%	1,925,359				
3047	ASPEN GROVE	IN	2,503,302	39.5%	2,464,916	2,503,302	39.5%	2,464,916	0	0.0%	0.0%	0
8156	CHERRY CREEK	IN	6,914,482	38.0%	10,632,813	6,914,482	38.0%	10,632,813	0	0.0%	0.0%	0
8560	FLATIRON CROSSING	IN	5,123,481	50.9%	6,996,628	4,790,454	47.5%	6,324,450	(333,026)	-6.5%	-3.4%	(672,179)
8261	PARK MEADOWS T/C	IN	5,106,277	29.1%	5,933,536	5,106,277	29.1%	5,933,536	0	0.0%	0.0%	0
3185	Southlands (APR)	IN	2,897,786	29.6%	3,002,647	2,897,786	29.6%	3,002,647	0	0.0%	0.0%	0
7651	Bel Mar (APR)	IN	2,762,584	21.4%	2,044,704	2,762,584	21.4%	2,044,704	0	0.0%	0.0%	0
80110	ENGLEWOOD	IN/OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
80014	AURORA	IN/OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
80038	NORTHLANDS	IN/OUT	0	0.0%	0	2,661,736	25.2%	2,183,230	2,661,736		25.2%	2,183,230
80111	GREENWOOD	IN/OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
Financials			**27,710,430**	**33.0%**	**33,000,603**	**30,039,140**	**31.9%**	**34,511,655**	**2,328,710**	**8.4%**	**-1.1%**	**1,511,052**

Highest NPV Scenario Compar

			BASELINE			SCENARIO 24 - Highest NPV			VARIANCE			
Store/Voids	Location Name	Evaluated	Year 0 Sales	IRR	NPV	Year 0 Sales	IRR	NPV	Year 0 Sales	Year 0 Sales % Change	IRR (ppt change)	NPV
8017	PEARL ST - BOULDER	OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
8444	DENVER FASHION PAV	IN/OUT	2,402,517	23.4%	1,925,359	2,347,259	22.7%	1,809,002				
3047	ASPEN GROVE	IN	2,503,302	39.5%	2,464,916	2,431,958	38.1%	2,324,770	(71,344)	-2.9%	-1.4%	(140,146)
8156	CHERRY CREEK	IN	6,914,482	38.0%	10,632,813	6,713,962	36.8%	10,139,255	(200,520)	-2.9%	-1.1%	(493,559)
8560	FLATIRON CROSSING	IN	5,123,481	50.9%	6,996,628	4,790,454	47.5%	6,324,450	(333,026)	-6.5%	-3.4%	(672,179)
8261	PARK MEADOWS T/C	IN	5,106,277	29.1%	5,933,536	4,815,220	27.2%	5,262,234	(291,058)	-5.7%	-1.9%	(671,302)
3185	Southlands (APR)	IN	2,897,786	29.6%	3,002,647	2,799,261	28.4%	2,788,640	(98,525)	-3.4%	-1.2%	(214,007)
7651	Bel Mar (APR)	IN	2,762,584	21.4%	2,044,704	2,762,584	21.4%	2,044,704	0	0.0%	0.0%	0
80110	ENGLEWOOD	IN/OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
80014	AURORA	IN/OUT	0	0.0%	0	0	0.0%	0	0		0.0%	0
80038	NORTHLANDS	IN/OUT	0	0.0%	0	2,661,736	25.2%	2,183,230	2,661,736		25.2%	2,183,230
80111	GREENWOOD	IN/OUT	0	0.0%	0	2,822,032	23.2%	2,407,733	2,822,032		23.2%	2,407,733
Financials			**27,710,430**	**33.0%**	**33,000,603**	**32,144,467**	**30.1%**	**35,284,017**	**4,434,037**	**16.0%**	**-2.8%**	**2,283,414**

Denver-Aurora / Scenario Summary / Output /

Figure 10. Denver selection results

E. CHAPTER SUMMARY

This chapter provided a basis for understanding real estate site selection processes utilized in industry. A model for this process was utilized showing the vast number of factors that need to be managed during this process. Additionally, four methods for factor management were presented. Of these four methods only three are capable of being optimized to provide maximum ROI in a given market (analog, regression, and spatial interaction). Optimization will be integral in truly ascertaining the optimal mix of locations in a given market. This chapter showed methods to analyze potential and current sites, however these methods only provide a means for looking at sites in isolation or with minimal impact for other sites. In order to gain a better understanding of the study area and how all sites interact with each other, further optimization is required. The next chapter will provide insight into artificial intelligent algorithms, specifically genetic algorithms, as a form of optimization. These optimizations will serve as a means to optimize multiple site locations within a market to produce maximum profit.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. APPLICATION OF ARTIFICIAL INTELLIGENCE

A. INTRODUCTION

As more companies enter an industry, competition for sales increases. Having a store in an optimal location can help with sales. In order to stay competitive companies are also going to have to become more efficient. Currently, companies are already optimizing store allocation and workforce. One area that many companies do not optimize yet is site selection.

This chapter will focus on methods to optimize site selections. Locating ideal sites through computer modeling may not be good enough in today's market. Finding ways to optimize all facets of an organization will be an important venture. Optimization utilizing artificial intelligence will afford three main objectives: (1) determine potential in the market, (2) highlight voids in the market where possible expansion could occur, and (3) maximize profit in the market based upon consumer actions. Using these three objectives as guides will allow a better understanding of the potential for artificial intelligent algorithms in optimization.

First, the aspect of optimization will be discussed. The example of real estate site selection in Denver, CO in the previous chapter will be used as a basis. Pitfalls in the previous example and ways to improve the process will be shown. Specifically, artificial intelligence for optimization will be discussed. This is the second portion of this chapter. Artificial intelligent algorithms can optimize site location analyses while handling all parameters needed. Genetic algorithms, a type of artificial intelligent algorithms, have been shown to be the most effect type of optimization. Currently, most companies are not optimizing at all. Improvements will be recommended for truly gaining an optimized location analysis.

B. OPTIMIZATION

In the previous chapter, four unique real estate site selection methods were discussed. Each method concentrated on one specific site in isolation. The output of a

spatial interaction model could possibly provide information on the following (Chipman, 2005):

- Sales
- Revenue transfer
- Trade area (or study area) extent

However, these spatial interaction model outputs are in isolation. Each model simulation reflects one possible scenario in a study area. The impact of multiple actions taking place in a given study area are not accounted for with tradition model outputs. In order to ascertain how multiple actions will affect the study area at the aggregate level, further optimization of model outputs needs to be conducted. Companies may want to look at how different actions will affect the revenue for a specific area. Deciding whether to open or close stores will depend on what is best for the study area in whole. Only looking at one action in isolation will not give enough information. Analysts would need to run a potentially large number of scenarios to account for all possible actions in a study area.

For example, within any given market a company could have 20 stores currently in existence. They could also be interested in an additional 20 potential sites to open. In order to fully analyze the market, an analyst would need to run a spatial interaction model for each possible scenario. Each scenario would show the affects of opening and/or closing stores in that particular market. The analyst would need to run every possible scenario and evaluate the potential of each scenario. Then, the analyst would need to compare all scenarios and determine which scenario was best for the given study area in order to find the optimal mix of open and closed stores. The market could potentially change within the amount of time it would take to run this many scenarios. However, methods are available to find an optimal market configuration. Artificial intelligent algorithms are such methods to optimize markets without analyst intervention. This would allow a company to account for all possible outcomes while producing an optimized mix new and existing stores within a potential market.

The scenario in the previous chapter is an example that could be optimized in order to determine the optimum market mixture of stores for the company. The results of

the example had the Northlands site opening and Pearl Street closing. However, this was based on 34 separate scenarios. The potential interactions between all sites were not evaluated. 34 scenarios were run which did not include every possible market configuration. The outcome was the optimal result based on the scenarios that were run, however this may not have been the optimal result for the market as a whole. Each scenario looked at one site and its affects on the surrounding sites in isolation. Artificial intelligent algorithms would have been able to run these scenarios in tandem allowing a model output that takes into account all possible actions. The decision to open the Northlands location and close Pearl Street may be the optimized result, however until the scenario is optimized the true answer will never be known.

There are many types of optimization techniques that are utilized to find a result for a given problem. However, depending on the type of problem at hand, the optimization technique utilized may not provide the desired results. Standard algorithms are a common means to find optimized results for problems. Algorithms are mathematical procedures with a finite set of instructions. They take an initial state, process them through the set instructions, and provide a finite end-state. An algorithm will look at a finite maximum or minimum based on the instructions provided. Unfortunately standard algorithms will not satisfy the real estate site selection problem due the problem's complexity. Complex problems, such as site selection, will generate many local maxima and minima. For this reason, more complex optimization procedures are required. These optimization procedures will be able to take into account local maxima and minima. The absolute maximum and/or minimum will be optimized for the problem.

1. Artificial Intelligence

Artificial intelligent (AI) algorithms can be used as an optimization technique to account for simplistic algorithm shortcomings. AI automates decision trees quickly alleviating the need for an analyst to conduct multiple scenario evaluations in isolation. Utilizing AI algorithms allows companies to optimize site allocation while including all pertinent parameters. Densham (1991) shows that AI algorithms are quicker than exact methods and can include multiple objective functions, or models, to analyze the data.

However, he also points out a drawback in the use of AI algorithms—they are not necessarily exact. These methods attempt to find absolute maxima and/or minima. The greater number local maxima and/or minima analyzed by the AI algorithm will provide a better estimate of the optimized solution to the site selection problem. Overall, AI algorithms can solve these problems quicker than traditional linear methods for problems with more than 25 existing sites (Houck, Joines, & Kay, 1996).

There are many types of AI algorithms available for solving the site selection problem. Each of these AI algorithms will need objective functions to obtain data. The models discussed in the pervious chapter represent the object functions required to feed into the AI algorithm. Figure 11 shows how the model output is fed into the artificial intelligent algorithm to obtain optimized results (Chipman, 2005).

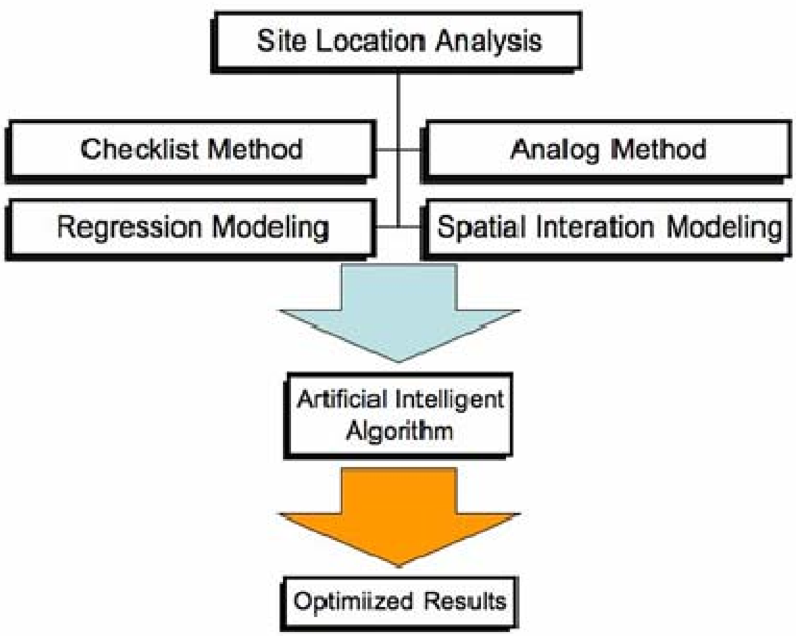


Figure 11. Application of Artificial Intelligence

The AI algorithm will take the model outputs and analyze the data to find local maxima and/or minima depending on the desired outcome of the scenario. If the goal was to maximize profit, maximums would be evaluated. If costs were to be minimized, minimums would be evaluated.

Three of the AI algorithms that could analyze this data are Random Restart, Two-Opt Switching, and Genetic Algorithms. This project will focus specifically on the use of genetic algorithms as a form of artificial intelligence. Genetic algorithms have been shown to "provide better solutions than either of the traditional procedures…and with less computational effort" (Houck et.al., 1996). When dealing with problems utilizing increasingly larger numbers of parameters demands, genetic algorithms have been shown optimize solutions quicker and with less computation power (Kim, 2001). In other words, genetic algorithms become more useful in optimization as the number of parameters increase. Other forms of AI algorithms require more computer power and take longer to complete.

The use of genetic algorithms has been seen as an advantage for over ten years. Church and Sorensen saw the potential for genetic algorithms in 1994 stating:

> Even though the genetic algorithm can produce extremely good results, solution times are usually much larger than other techniques. Such a process might be a candidate when computational resources are very large…

This was written in 1994. At that time researches were first realizing genetic algorithms and their potential. Houck, Joines, and Kay (1996) also were able to prove the potential for genetic algorithms. They performed seven tests specifically designed to show quality of the solution obtained and the computational efficiency for the solution. Smaller-sized problems (less than 25 initial sites) showed little performance difference in multiple AI methods. However the ability of genetic algorithms, specifically through the use of genetic crossover operations, to obtain a better solution by combining parts of two existing solutions provided more optimal solutions overall with equivalent computational effort. For these reasons, only genetic algorithms will be examined in this project.

2. Genetic Algorithms

> Genetic algorithms were founded on the principle of biological evolution, such as survival of the fittest. Genetic algorithm techniques are applicable to many difficult optimization problems by using evolutionary parameters (i.e. population and generation sizes), genetic operators (i.e. crossover and mutation) and other evolution control criteria (i.e. selection, pressure, termination condition and fitness scaling). (Kim, 2001).

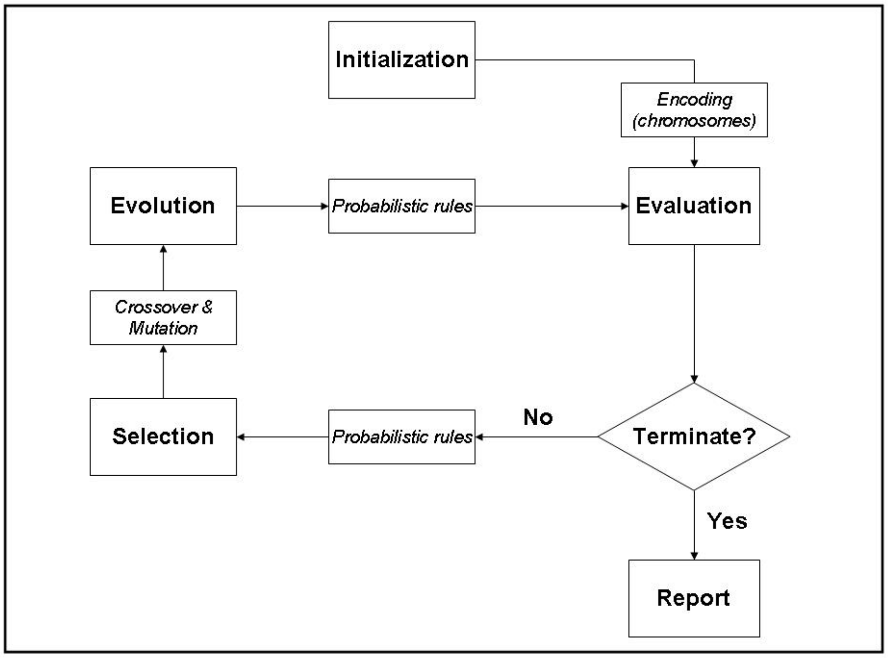
Young-Hoon Kim's quote describes genetic algorithms in a context showing similarities to biological evolution. This is the basis for genetic algorithms. If an optimization is not better than its predecessors, it is thrown out. Conversely, if the solution is better than its predecessors, it is kept. This process continues until an optimal optimum solution is provided.

Hurley, Moutinho, and Stephens (1995) illustrate the use of genetic algorithms with goal of solving the following three expectations:

1. Identify the appropriate number of sites to use within a market.
2. Identification of sites to be removed from the exiting network of stores or sites. In other words, identify sites that should be closed to obtain an optimum market based on consumer actions.
3. Find the best subset of sites to market a specific product or service. This could be retail clothing, restaurants, oil-change stores for cars, or any other product or service desired by the company.

These expectations are best sought after when analyzing a market that contains multiple current and potential sites. Hurley et al. (1995) base their examples on a study area with 50 or more sites and several other proposed sites. This does not mean that results will be incorrect for smaller markets. This solely means that larger markets need to be analyzed in greater depth and that genetic algorithms can do a great deal of the work for the analyst in a relatively shorter amount of time.

Figure 12 outlines the flowchart in the process for genetic algorithms (Kim, 2001). Kim shows the basic structure of genetic algorithms during computations. These algorithms treat each problem as an evolutionary sequence. Ultimately, if the output is evaluated as more desirable than the initialization the process will terminate. Termination will be based upon pre-defined termination rules. However, this process must be run for every possible scenario.



Source: Young-Hoon Kim's *Identifying evolutionary searching mechanism of genetic algorithms for regional science modeling* from the Sheffield Centre for Geographic Information and Spatial Analysis (SCGISA), 2001.

Figure 12. Genetic Algorithm Structure Flowchart

Within the genetic algorithm flowchart each block represents a function of the computerized process. Each time the genetic algorithm goes through this process a new generation is created. One cycle through the flowchart is considered a generation. Kim (2001) continues to explain the nomenclature for this process. The AI algorithm gains its nomenclature from biological terms. The initial set of for the random solution is called the population. A population is made up of a set of chromosomes. Each chromosome represents a set of locations which are called genes. A gene in a given chromosome can be represented by a binary bit that can be switched on (1) or off (0). The following is an example of a potential chromosome that has 10 sites:

1001100101 (10-site chromosome)

This chromosome is made of 10 genes that represent sites in a study area. The first binary digit on the left is a "1". This means that site 1 is open. The second binary digit from the left is a "0". This means that site 2 is closed. This chromosome is a potential solution for a study area of 10 sites.

a. Initialization

The initialization creates the starting point for the genetic algorithm in the process. The required data for a given market or study area can be formulated randomly or by using specific information about the problem at hand. At this stage the analyst will set up rules for the genetic algorithm. The number of chromosomes in the population, crossover and mutation data (to be discussed later), and termination rules will all be set up during the initialization process. Once the population is initialized, the chromosomes can be encoded.

b. Encoding

Each individual site in the population is represented by genes. Chromosomes will have sites encoded as on or off depending on the initialization rules. This is only a starting point for the optimization process. As the process progresses, chromosomes will be examined and changed based upon pre-determined rules while searching for an optimized outcome.

c. Evaluation

Each chromosome in the population is evaluated against set probabilistic rules. Chromosomes that produce better outcomes for the study area have a great chance of being selected for the next generation. Less superior chromosomes will be discarded. However, each evaluation creates local maxima and/or minima. This means that just because a set of chromosomes are optimal in one generation, they may not be optimal in the next. To prevent a local maximum from occurring, some less optimal chromosomes will survive the evaluation and move on to the next generation.

d. Probabilistic Rules

The probabilistic rules come from the models discussed in the previous chapter. These objective functions test the chromosomes for their suitability. As the genetic algorithms progress, the overall suitability, fitness, of the better chromosomes should increase. Also, the overall fitness of the population in general should increase as future generations are created.

In the case of site selection, a company would be looking to maximize revenue by opening and/or closing stores to obtain an optimum mix of stores in a market. At the same time, the company would also want to minimize the impacts of cannibalization. This can be done through the use of site selection models discussed in the previous chapter looking to examine sales forecasts and/or cannibalization.

If the genetic algorithm was looking to optimize sales forecast, it could use an analog model for its probabilistic rules. Each gene in a given chromosome would be evaluated against a set of analogous sites. The gene, or site, would be assigned a revenue based upon the existing set of similar stores in the analog database. Each gene's revenue in the chromosome that is turned on, set at 1, would be utilized to determine the fitness of the chromosome.

e. Crossover and Mutation

During this phase, new chromosomes are formed. These new chromosomes may carry traits similar to their parent chromosomes. Crossover and mutation represent the evolutionary aspect of genetic algorithms by simulating the biological process of genetics. Just as a male and female human pass along genetic traits to their children via evolution, chromosomes within genetic algorithms will pass along specific traits to future generations based upon crossover and mutation.

1) Crossover. Crossover merges two chromosomes from the current generation. This will take two separate chromosomes and merge parts of each to create a new chromosome (child). De Jong (1975) has shown through empirical studies that that better results are ultimately achieved when crossover probability is between 0.65 and 0.85. In other words, the probability that a chromosome will continue to the next generation is between 0.35 and 0.15. The majority of chromosomes will end up with a crossover while only a minority (0.15 - 0.35) will move to the next generation unchanged. Standard crossover is one-point crossover where two selected parents would crossover at a randomly selected point:

Parent 1: X_1, X_2, X_3, X_4, X_5

Parent 2: Y_1, Y_2, Y_3, Y_4, Y_5

Hypothetical crossover at point 3

Child 1: X_1, X_2, X_3, Y_4, Y_5

Child 2: Y_1, Y_2, Y_3, X_4, X_5

This shows the two children with the fourth and fifth positions crossed over from their parent's original chromosome set.

2) Mutation. Mutation signifies the computer modifying a chromosome. Just by switching a single gene in a chromosome on or off, a new chromosome will be formed. If both parents had position two set off, then all children would have this same off position for position two. Mutation prevents this from occurring. Mutation will randomly switch genes from off to on and vice versa. This is generally done infrequently (1 in 1000).

f. Evolution

A new set of chromosomes is ready to be analyzed based upon crossover and mutation. This new set of chromosomes has evolved and can be fed into the probabilistic rules again to create a new generation of chromosomes. The same probabilistic rules will be utilized during this stage of the process as previously utilized. At this point, the new generation must be reevaluated to determine whether the new generation is more optimal than the previous.

g. Termination

Eventually the genetic algorithm will terminate. There are two ways that the algorithms will stop producing future generations. During the initialization procedures, the analyst will set a pre-determined number of generations to process. The genetic algorithm will process the set number of generations then terminate with a result. The other way the process will terminate is based upon the level of improvement from one generation of chromosomes to the next. If there is no statistically significant improvement between subsequent generations, the genetic algorithm will terminate.

C. OPTIMIZING SITE SELECTION UTILIZING GENETIC ALGORITHMS

Optimization can lead to efficiencies. In other words, an optimized organization is efficient. Many companies understand that site location is a part of this optimization

process. This chapter has focused on providing a means to optimize the real estate site selection process. Site selection models can be fed into genetic algorithms for optimization. The type of model utilized is practically irrelevant with optimization. Taking a valid model output and imputing it into an artificial intelligent algorithm for optimization is the key. The use of artificial intelligent algorithms, specifically genetic algorithms, can provide an improved decision aid in the real estate site selection process. The following example will provide a basis for how this optimization would affect possible decisions.

1. Sample Genetic Algorithm

A simple example (Hurley, Moutinho, & Stephens, 1995) of how genetic algorithms work is presented to show the artificial intelligent evaluation process in practice. For this five potential chromosomes will be initially evaluated (initialization).

C_1	1010011
C_2	0011110
C_3	1010001
C_4	1111000
C_5	1110101

There will be four existing sites and 3 potential sites to be evaluated. Each of the genes in the chromosomes represents whether a site would be open or closed. The first four genes from left to right represent the four existing stores. The last three represent the potential new stores. C_4 shows that all four existing stores would remain open; while the three new stores would not open.

For this hypothetical example, the analog model will be utilized for the probabilistic rules. Each chromosome would be run through the analog model to ascertain its fitness level. The fitness level would be the total revenue expected for a market based upon the assigned open and closed stores. Each gene in the chromosome would be defined by the revenue for an analog of similar sites in the company's databases. For C_2 this would mean that the revenues approximated for the four sites 1, 2, and 7 being closed while 3, 4, 5, and 6 were open. The hypothetical outputs are as follows:

C_1	1010011	fitness = 10,542
C_2	0011110	fitness = 12,321
C_3	1010001	fitness = 13,222
C_4	1111000	fitness = 11,214
C_5	1110101	fitness = 10,499

Since chromosomes C_2 and C_3 have the highest fitness, they would be the most likely subjects for crossover and mutation. If one-point crossover randomly was chosen at point 5, the following children would be produced:

C_2	0011001
C_3	1010110

These two children chromosomes would then be put through the analog model (probabilistic rules) to come up with the following hypothetical outputs:

C_2	0011001	fitness = 11,229
C_3	1010110	fitness = 14,017

This shows that there is now a network of sites, represented by C_3, which is theoretically better than all previous chromosomes in the population. This does not take into account any mutation at this point. Mutation could possibly bring about "fitter" solutions.

This process will be run multiple times as dictated by the analyst until optimum optima are produced. The computational power required for this analysis can be rather cumbersome. As computer power increases and comes more readily available, this type of analysis will also become easier to conduct.

2. Example of Genetic Algorithms in Practice

Genetic algorithms have previously been used in operation, although many times genetic algorithms require more computing power than is available for computation. As the price of computing speeds decrease, the potential use of genetic algorithms for optimization in real estate site selection can increase. Few practical real estate site selection examples are available.

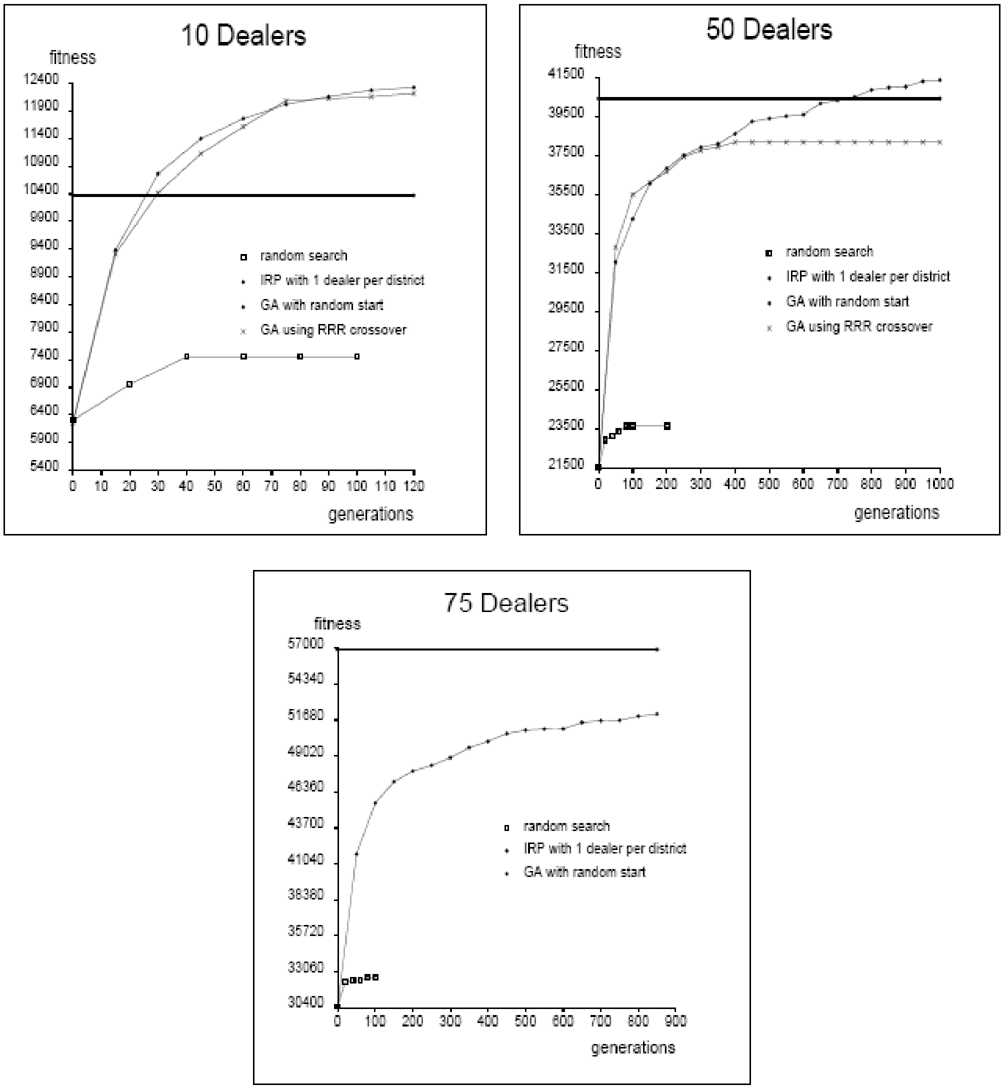
The following example provided by Felicity George (1994) shows the advantages of using genetic algorithms versus another heuristic optimization technique for optimizing networks of car dealerships in England. GMAP Ltd.'s heuristical optimization model called the idealized representation plan (IRP) and genetic algorithms were both used to optimize a network of car dealerships. Spatial interaction models acted

as probabilistic rules within each optimization. Ultimately the fitness of each technique was compared after a specified number of generational computations.

The car company had previously utilized the IRP model to optimize its network of dealerships. The IRP model is another heuristic algorithm. This algorithm selects data points that are profitable but may not combine together to produce an optimal network. IRP optimization work best when taking a larger set of locations in order to provide a great set of combinations to analyze. The ultimate fitness of generations would be the ultimate guide to determine if there was a clear advantage to genetic algorithms over other techniques. The greater the fitness of a generation would imply a greater profit from the optimized dealership network. In other words, both techniques would produce multiple generations. George conducted this experiment with various termination rules. Networks of dealerships with 10, 50, and 75 locations were utilized to see if there was a noticeable difference in overall fitness.

Figure 13 shows the optimization outputs of the three runs. For dealership networks of 10 and 50 locations, a genetic algorithm optimization provides a higher fitness than the IRP and random search techniques. When George examined only a 10 dealership network, genetic algorithms consistently outperformed other techniques after 30 generations. This increased up to about 110 generations where an apparent maximum fitness is reached. When George increased the dealership network size to 50 dealers, genetic algorithms outperformed the other techniques only when RRR crossover was utilized. RRR crossover is a type of genetic crossover utilized within the genetic algorithm operators.

The optimization with 75 dealership locations showed a different output. The IRP solution provided a greater fitness after 850 generations (based upon termination rules). However, these results should be examined more closely. George stated that time was too limited to run the genetic algorithms beyond 850 generations stating that it took over 17 hours to complete 850 generations on the computing machines in 1994. Although genetic algorithms did not outperform the IRP after 850 generations, they were still progressing at a increasing rate. Eventually, if a greater time for termination was set, genetic algorithms could possibly out-perform IRP solutions for greater networks.



Source: Felicity George's *Hybrid Genetic Algorithms with Immunisation to Optimise Networks of Car Dealerships* from the Edinburgh Parallel Computing Centre, 1994.

Figure 13. Networks of 10, 50 and 75 dealerships

The difference in fitness within each graph could represent profit for the company. If the automotive company had used a random search or IRP technique for optimization, they could have missed \$500,000 or \$200,000 respectively depending on which technique they could utilized for a network of 10 dealerships. The missed profit is noticeable for each scenario. However, increased computer speed that was not available in 1994 is available today for the average real estate analyst. Scenarios with over 75

dealerships can be examined today with much quicker speeds. Utilizing the optimal site selection optimization technique is a means to help identify the optimal network of sites for a company in a study area.

3. Optimizing Real Estate Site Selection in Practice

Optimizing the real estate site selection process aims to accomplish two tasks: maximize company profit in a specified market and eliminate opening "dogs". Dogs represent locations that are not profitable or feasible for an organization. "Dog" stores generally will be closed in the future. A company would want to avoid "dog" locations. The costs to acquire a location, build the site, train personnel, and supply product can be large. Closing a location requires even more money and can lead to huge losses in a market. Avoiding "dog" locations can be very desirable to many companies.

Optimizing real estate site selection through the use of genetic algorithms presents value to companies looking to optimize their network of locations. As discussed earlier, companies can help maximize their profits through genetic algorithms. Companies can also help to eliminate opening "dog" locations. However, how much is this optimization of profit worth to a company? This is the question that drives the value of this optimization within a company.

The concept of utilizing AI algorithms to optimize the real estate site selection process is new. Very few companies are using this technique. Training personnel on AI intelligent algorithms as a means of optimization may not be the best avenue for companies to gain this real estate advantage. Hiring third-party consultants may be a better means to obtain this service.

D. CHAPTER SUMMARY

As competition increases in markets, efficiencies will need to be made throughout all levels of organizations. Site locations will need to be optimized. Gaining an edge through optimized site locations can become a new market in itself. This chapter provided an insight into an optimization technique for real estate site selection. There are many techniques available to optimize results; however only artificial intelligence was

discussed. Specifically genetic algorithms as a form of artificial intelligence were shown to be the most effective form of optimization. Genetic algorithms provided the most comprehensive form of artificial intelligence requiring the least amount of time for results. As the cost of computing decreases, genetic algorithms will be even easier to utilize. More and more companies and consulting firms will be able to utilize this form of optimization as this concept gains acceptance.

V. SUMMARY AND RECOMMENDATIONS

A. SUMMARY

The goals of this project, as stated in the introduction, were to answer the following questions:

1. Primary Questions

- Is there a current need for market planning modeling? If so, why?
- To what extent do artificial intelligent algorithms improve the market planning process?
- Can artificial intelligent algorithms be applied successfully to market planning?

2. Secondary Question

- What are the limitations to current market planning models?

These questions were answered in this project providing insight into real estate site selection techniques and ways to optimize selection through artificial intelligence.

Market planning modeling is currently needed. Markets are becoming more complex with new competitors emerging. To stay competitive in the market, companies can utilize computer models such as analog, regression, and spatial interaction models. These will help companies manage multiple parameters while giving them insight previously unavailable through the checklist method.

Adding artificial intelligent algorithms, specifically genetic algorithms, to a company's real estate site selection process makes sense. Optimizing location analysis enables a company to gain efficiencies in site locations, hence providing a competitive edge. Saving money can generate increased profit even without increased revenue. Also, potentially avoiding the opening of bad site locations is a huge savings. The small investment in optimized site location analysis can save money in the future.

Genetic algorithms have been applied in market planning. Unfortunately, only theoretical data is provided to show quantifiable improvements in optimization. However

these improvements should increase the competitive edge for companies utilizing their benefits. The market planning example shown in Colorado did not account for all possible parameters in that market. Possible over-estimates were created in their analysis that could provide bad data to be carried forward in future analyses. An optimization of the model data would have helped to minimize bad data.

Current market planning models do require some technical knowledge and computing power. Unfortunately, not many companies employ personnel capable of creating these models. Also, companies may not have the requisite computing power needed to run these models and optimization techniques.

One method that small and medium sized companies could employ to gain the same efficiencies in real estate site selection as large companies is to hire third-party consultants. Outsourcing real estate site selection or the optimization of the process could prove to be more cost effective. This would allow companies to focus on their core competencies with their existing workforce.

B. APPLICATION TO MILITARY RETAIL FACILITIES

Current military retail facilities are aligned with military bases. Size and allocation are dependent upon base size and location. The Navy Exchange Command could benefit from this research by utilizing site selection models and optimization techniques. Data could easily be gathered from POS transactions at each facility.

POS data could be fed into a spatial interaction model utilizing standard data. This would enable the Navy Exchange Command to see how their shoppers are truly interacting with the military facility as opposed to commercial stores. Optimizing model output through a genetic algorithm would allow the Navy to optimize store allocation, location, size, and sales. In a time where the United States military is seeking efficiencies in all areas, this could prove useful.

C. LIMITATIONS TO THIS WORK

1. Market Research

Further in-depth market research could be conducted in order to gain a broader sense of current real estate site selection processes. This project solely analyzed a few companies in various industries. More research within each industry would provide a better understanding of industry-specific issues that are not fully addressed within this project.

2. Optimization Complexities

Optimization via artificial intelligence is a complex and evolving field of study. Innovations and advances are constantly being implemented to gain advantages in business. Due to the fast-paced culture of this field and it's evolving nature, not all modeling complexities were mentioned.

D. SUGGESTIONS FOR FUTURE RESEARCH

This project looked solely at current real estate site selection techniques and a possible method of improved optimization—artificial intelligent algorithms. A more in-depth analysis of other industries may provide information on the overall effectiveness of genetic algorithms. Specifically an artificial intelligent application could be developed to test the validity of this approach to optimization. This application could be compared to initial non-optimized model output and other optimization techniques. This comparison would be able to provide a true quantitative analysis of the various site selection and optimization techniques.

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

ARTICLES & PROFESSIONAL REPORTS

Applebaum, W. (1966). Methods for Determining Store Trade Areas, Marketing Penetration and Potential Sales. *Journal of Marketing Research, 3*, 127-141.

Alt, W. (1967). Junior College Campus Sites—How to Save Money. *Aspects of the College, Brief-7.*

Bennett, S. (2003). Venturing into Fast-Lube. *National Petroleum News, Vol. 95 Iss. 7,* 18-25.

Bergeron, C. (2005). Making site selection decision in the worldwide economy. *Handbook of Business Strategy,* 89-94.

Bibb, R. (2001). Site-Location Analysis. *Retail Merchandiser, Vol. 41 Iss. 4,*70.

Blazer, T. (2001). Finding the right site: Technology and demographic data improve retail site searches. *Commercial Investment Real Estate Journal, Vol. 20 Iss. 2,* 34.

Brown, T. (2004). Opportunities Abound. *Chain Store Age, Vol 80 Iss. 6,* 83.

Brubaker, B. (2004). Site Selection Criteria in Community Shopping Centers: Implications for Real Estate Developers. Submitted to the Department of Agriculture in partial fulfillment of the requirements for the degree of Master of Science in Real Estate Development at the Massachusetts Institute of Technology, September 2004.

Buckner, R. (1998). *Site Selection: New Advancements in Methods and Technology.* New York, NY: Chain Store Publishing Corp.

Buss, D. (2002). Retailers focus new attention on site-selection process. *Stores, Vol. 84 Iss. 5*, 54.

Buxton, T. (2005). Beyond Demographics. *Commercial Investment Real Estate, Vol. 24 Iss. 4*, 16.

Carter, C., & Vandell, K. (2005). Store Location in Shopping Centers: Theory and Estimates. *The Journal of Real Estate Research, Jul-Sep, 27,* 237-266.

Castle, G. (Ed.). (1993). *Profiting from a Geographic Information System.* Fort Collins, CO: GIS World.

Chittum, R. (2005). Office Technology; Location, Location, Technology: Where to put that new store? Site-selection software may be able to help. *The Wall Street Journal, July 18,* R7.

Church, R. L., & Gerrard, R. (2003). The Multi-level Location Set Covering Model. *Geographical Analysis, Vol. 35, No. 4*, 277-289.

Church, R. L., & Sorensen, P. (1994). Integrating normative location models into GIS: Problems and prospects with the p-median model. *National Center for Geographic Information and Analysis, Technical Report 94-5.* Santa Barbara: University of California at Santa Barbara.

"Company X" Research Project: Normal Curve Sales Potential Model Milestone. (2004, June 17). Research report provided by a "Company X" employee January 2005. "Company X" is a well-known retail company that shall remain confidential for this project as per the employee's request. For the identity of "Company X", please contact the project author personally.

Czinkota, M., & Kotabe M. (2005). *Marketing Management (3rd ed.).* Cincinnati, OH: Atomic Dog Publishing.

Daniel, L. (1994). GIS Helping to Reengineer Real Estate. *Earth Observation Magazine, November 1994.*

De Jong, K. (1975). An analysis of the behavior of a class of genetic adaptive systems. Doctoral dissertation, University of Michigan, *Dissertation Abstracts International*, Vol. 36 No. 10.

Densham, P., & Rushton, G. (1991). Designing and Implementing Strategies for Solving Large Location-Allocation Problems with Heuristic Methods. National Center for Geographic Information and Analysis, Report 91-10.

Des Rosiers, F., Theriault, M., & Menetrier, L. (2005). Spatial Versus Non-Spatial Determinants of Shppoing Center Rents: Modeling Location and Neighborhood-Related Factors. *The Journal of Real Estate Research, Jul-Sep, 27,* 293-319.

Fryrear, R., Prill, E., & Worzala, E. (2001). The Use of Geographic Information Systems by Corporate Real Estate Executives. *The Journal of Real Estate Research, Jul-Oct 2001, 22,* 153-164.

George, F. (1994) Hybrid Genetic Algorithms with Immunisation to Optimise Networks of Car Dealerships. Edinburgh Parallel Computing Centre, University of Edinburgh, England.

Gibler, K. (2004). Agency Risks in Outsourcing Corporate Real Estate Functions. *The Journal of Real Estate Research, Apr-Jun 2004, 26,* 137-160.

Gibler, L., Black, R., & Moon, K. (2002). Time, place, space, technology and corporate real estate strategy. *The Journal of Real Estate Research, Nov/Dec, 24,* 235-263.

Houck, C. R., Joines, J. A., & Kay, M. G. (1996). Comparison of Genetic Algorithms, Random Restart, and Two-Opt Switching for Solving Large Location-Allocation Problems. *Computers & Operations Research, 23(6),* 587-596.

Holland, J. (1975). *Adaptation in Natural and Artificial Systems.* Ann Arbor, MI: University of Michigan Press.

Hosage, C., & Goodchild, M. (1986). Discrete space location-allocation solutions from genetic algorithms. *Annals of Operations Research, 6*, 35-46.

Huff, D. (1964). Defining and Estimating a Trade Area. *Journal of Marketing, 28,* 34-38.

Hurley, S., Moutinho, L., & Stephens, N. M. (1995). Solving marketing optimization problems using genetic algorithms. *European Journal of Marketing, Vol. 29 No. 4,* 39-56.

Karakaya, F., & Canel, C. (1998). Underlying dimensions of business location decisions. *Industrial Management & Data Systems, 98/7,* 321-329.

Kates, S. (1997). Real Estate Site Selection Using GIS and MCDM: A Case Study of the Toronto Retail Jewelry Industry. Submitted in partial fulfillment of the requirements of Master of Arts, Faculty of Graduate Studies, The University of Western Ontario. London, Ontario, Canada.

Kim, Young-Hoon. (2001). *Identifying evolutionary searching mechism of genetic algorithms for regional science modeling.* Regional Science Association International: Brittish and Irish section, 31st annual conference, Durham Castle, 5-7 September 2001. Sheffield, England: Sheffield Centre for Geographical Information and Spatial Analysis (SCGISA), University of Sheffield.

Kotler, P. (1984). *Marketing Management: Analysis, Planning, and Control, (5th edition.* Englewood Cliffs, NJ: Prentice-Hall, Inc.

Konrath, J. (2005). How to Write a Strong Value Proposition. *The Sideroad: Your Road to Expert Advice.* Retrieved November 5, 2005 from http://sideroad.com/Sales/value_proposition.html

Lea, A. (1989). An Overview of Formal Methods for Retail Site Evaluation and Sales Forecasting: Part 1. *The Operational Geographer, 7.2,* 8-17.

Lea, A., & Menger, G. (1990). An Overview of Formal Methods for Retail Site Evaluation and Sales Forecasting: Part 2. *The Operational Geographer, 8.1,* 17-23.

Lee, M., & Pace, R. (2005). Spatial Distribution of Retail Sales. *Journal of Real Estate Finance and Economics, Vol. 31 Iss. 1,* 53.

Lilien, G., & Kotler, P. (1983). *Marketing Decision Making—A Model Building Approach.* New York: Harper & Row.

Mendes, A. B., & Themido, I. H. (2004). Multi-outlet retail site location assessment. *International Transactions in Operational Research, 11.* Pnta Delgada, Portugal: Azores University.

Muller, C., & Inman, C. (1994). The Geodemographics of Restaurant Development. *The Cornell Hotel And Restaurant Administration Quarterly, Vol. 35, No. 3,* 88-95.

Neslon, R. (1958). *The Selection of Retail Locations*. New York: F. W. Dodge Corp.

Nwogugu, M. (2004). Corporate governance, strategy and corporations law: The case of Jack in the Box Inc. *Managerial Auditing Journal, Vol. 19, No. 1,* 29-67.

O'Malley, L., Patterson, M., & Evans, M. (1995). Retailing applications of geodemographics: a preliminary investigation. *Marketing Intelligence & Planning, Vol. 13, No. 2,* 29-35.

Pace, R., Barry, R., & Sirmans, C. (1998). Spatial Statistics and Real Estate. *Journal of Real Estate Finance and Economics, Vol 17, Num 1,* 5-13.

Parks, L. (2004). Nectar Finds Loyalty's Sweet Spot. *Stores, Vol. 86, Iss. 7,* 66.

Pollo Tropical Spreads its Wings with Aggressive Expansion Plans Based on MapInfo Location Intelligent Solutions. (2005, June 9). *Business Wire.* Retrieved November 1, 2005, from http://www.businesswire.com

Rabianski, J., DeLisle, J., & Carn, N. (2001). Corporate real estate site selection: A community-specific information framework. *The Journal of Real Estate Research, Jul-Oct, 22,* 165-198.

Perlik, A. (2004). Grow With the Flow. *Restaurants and Institutions, September 15.*

Reda, S. (2003). At Lacoste, site selection is key to achieving profitability within a year. *Stores, Vol. 85 Iss. 4,* 52.

Nelson, R. (1958). *The Selection of Retail Locations.* New York, NY: F.W. Dodge Corp.

Sulek, J., Lind, M., & Marucheck, A. (1995). The impact of a customer service intervention and facility design on firm performance. *Management Science, 41 (11),* 1763-1773.

Summerour, J. (2003). Site Selection in the Wal-Mart Age. *Progressive Grocer, Vol.82 Iss. 5,* 37-38.

Thompson, D. (1966). Future Directions in Retail Area Research. *Economic Geography, 42*(1), 1-18.

Xiao, N., Bennett, D. A., & Armstrong, M. P. (2002). Using evolutionary algorithms to generate alternatives for multiobjective site-search problems. *Environment and Planning, volume 34,* 639-656.

Zache, R. (2000). Developing a new approach. *Commericial Investment Real Estate, Vol. 19 Iss. 2,* 46.

INTERVIEWS

Chipman, David. Real Estate Analyst, Gap Inc. Interviewed by LT Eric L Shangle, personal interview, 31 July 2005, 2:00pm, Starbucks, Del Rey Oaks, CA.

Davis, Suzy. Real Estate Research Assistant, Alex Lee, Inc. Interviewed by LT Eric L Shangle, phone interview, 11 October 2005, 11:05am, Fleet Numerical Meteorology and Oceanography Center, Monterey, CA.

Smith, James. Location Research Support, White Castle Management. Interviewed by LT Eric L Shangle, phone interview 12 October 2005, 8:30am, Fleet Numerical Meteorology and Oceanography Center, Monterey, CA.

Young, Kevin. Project Manager, JCPenney. Interviewed by LT Eric L Shangle, phone interview, 11 October 2005, 2:20pm, Fleet Numerical Meteorology and Oceanography Center, Monterey, CA.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California