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EVALUATION OF OPTIMIZATION ALGORITHMS FOR IMPROVEMENT OF A TRANSPORTATION COMPANIES (IN-HOUSE) VEHICLE ROUTING SYSTEM

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EVALUATION OF OPTIMIZATION ALGORITHMS FOR

IMPROVEMENT OF A TRANSPORTATION COMPANIES (IN-HOUSE)

VEHICLE ROUTING SYSTEM

By

Jian Han

A Thesis

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EVALUATION OF OPTIMIZATION ALGORITHMS FOR

IMPROVEMENT OF A TRANSPORTATION COMPANIES (IN-HOUSE)

VEHICLE ROUTING SYSTEM

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University of Nebraska, 2010

Adviser: Erick C. Jones

Vehicle routing problem (VRP) is the main issue of the transportation. It is becoming more and more popular. Trucking companies play an important role in the transportation industry. Most trucking companies are developing their own software to make profit. Often, the software is used for routing optimization models to minimize cost because the first work is organized over the road.

Linear Programming and saving heuristics are traditional algorithms for solving the vehicle routing problems. However, none of the companies want to make a decision of routing by calculating with mathematics models in their companies. So the vehicle routing software is being used in the trucking company. This paper will present two traditional models and one in-house vehicle routing optimization software, running the same data, then compare the result, and see the results of each model. The results of the data demonstrated the best model was located in the in-house optimization software. This research approach can be used in the similar companies.

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Chapter 1 Introduction

Introduction

For the trucking companies, work is organized for transporting inventory efficiently over the road. They make a profit by shipping goods for customers from one location to another. Truck drivers operate either independently or by working directly for the client through freight carriers or shipping agents. Over the road freight movement has advantages of requiring cheaper investment funds, having high accessibility, mobility and availability (Yung-yu et al. 2005). Vehicle routing may be decided by people who are working in the office. Historically, the transportation companies that were smaller could perform vehicle routing without optimizing computer application. Currently the transportation industry has larger operation that requires complex project approaches. In order to optimize vehicle routing, a company needs to vehicle capacity, departure and arrival times and the number of miles driven. Some software companies, such as Direct Rout®, present offerings to solve this problem.

From 2008, almost all the world has suffered a financial down turn unlike any since the 1920s. The global financial crisis has taught us one thing: simply moving money from account to account doses not produce prosperity. However, good life depends on building up economic activities that deliver goods and services to the real people, when and where they need them (Janice Party ka et al. 2010). So, new technology is required to be used in the current industrial area. Routing software companies are offering creative ways to integrate computer, communication and location technologies with algorithms and software, helping industries find a period of recovery. These technologies enable

routing software companies to provide sophisticated connectivity and productivity tools to an increasingly mobile workforce and widely distributed customers. Many of the routing companies know that it is unsuccessful to manage a company that runs everything by mathematicians. Customers are looking for stability and distribution system expertise more than the latest algorithms. Nevertheless, one of the challenges is that all of these companies will face is the ability to process data to re-optimize routes in real-time. With map data getting richer and real-time traffic adding road segment data in small time intervals, the processing requirements will grow substantially. The underlying architecture of these offerings and how the processing is distributed will be a critical factor in how well each product fares. In this research, we have attempted to evaluate and compare the benefits of the traditional vehicle routing model algorithms and business vehicle routing software. We then found the best model to improve the business vehicle routing software, in order to make more profits for the truck companies.

Chapter 2 Objective and Problem Statement

The research objective is to demonstrate how two traditional algorithms compare to the trucking company's in-house algorithm. We ran the same data in all of the models and software, in order to find the different results. Then, we preformed an analysis to find the best model. The research focused on an overall research question and two specific objectives in order to achieve our answer research questions. It is constructed in the following way.

2.1 Overall Research Question

What is the best algorithm for optimizing an in-house vehicle routing system (VRS)?

2.2 Specific Objectives

1) Identify which optimization algorithms can improve an in-house vehicle routing system (VRS).

2) Evaluate the performance differences of the optimization algorithms for the vehicle routing system (VRS).

Chapter 3 Background

3.1 Vehicle Routing Problem (VRP) Basics

3.1.1 Vehicle Routing Problem Definition

The vehicle routing problem (VRP) is a combinatorial optimization and integer programming problem seeking to service a number of customers with a fleet of vehicles. Actually, VRP is a generic name which is given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or more depots must be determined for some geographically dispersed cities or customers. Proposed by Dantzig and Ramser in 1959, VRP is an important problem in the fields of transportation, distribution and logistics (Dantizig 2008). The objective of the solution to the VRP is that of delivering goods located at a central depot to customers who have placed orders for such goods. Implicit is the goal of minimizing the cost of distributing the goods. Many methods have been developed for searching for good solutions to the problem, but for all but the smallest problems finding a global minimum for the cost function is computationally complex. As we know, vehicle routing is a combinatorial optimization problem. The problem is that a trucking service has to service a set of customers at different sites within specified time intervals. So, the goal is to maximize the number of customers serviced, while satisfying the timing constraints. In the two figures below, two types of typical input for a VRP problem and of its possible outputs are presented.

Figure 1 Typical For a Vehicle Routing Problem
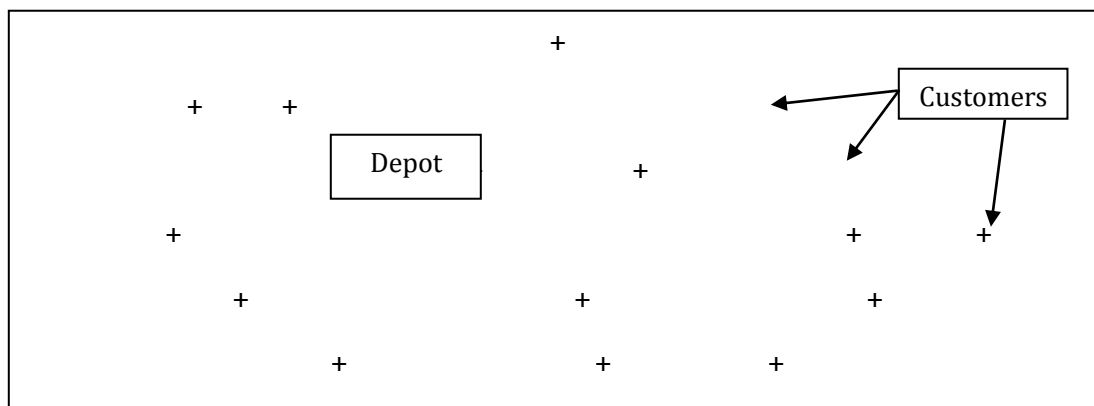
Figure 2 Output for the Instance Above
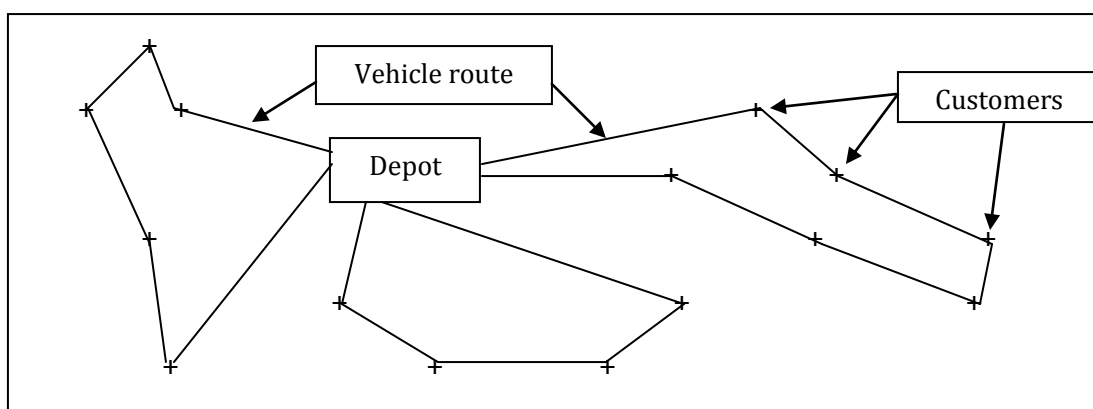
3.1.2 Why The VRP Is Important in The Transportation Industry

Transportation is an important area of human activity in the modern society. It supports and makes possible most other social and economic activities. Whenever we use a telephone to call our family members, shop at a food store with our parents, read our mail or fly for business or pleasure, we are the beneficiaries of some system that has routed messages, goods or people from one location to another. Freight transportation, especially,

is one of today's most important activities. Here are some surveys of annual costs of excess travel in the United States. It has been estimated that some USD 45 billion has been wasted (King and Mast, 1997). The turnover of transportation of goods, by the U.S, in Europe is some USD 168 billion per year. "Also, in the United Kingdom, France and Denmark, for example, transportation represents some 15%, 9% and 15% of national expenditures respectively (Crainic and Laporte 1997; Larsen 1999)". It is estimated that distribution costs account for almost half of the total logistics costs and in some industries, such as in the food and drink business, distribution costs can account for up to 70% of the value added costs of goods (De Backer et al. 1997; Golden and Wasil 1987) Halse (1992) reports that in 1989, 76.5% of all the transportation of goods was done by vehicles, which also underlines the importance of routing and scheduling problems.

3.1.3 Vehicle Routing Problems With Time Windows

Routing and scheduling problems are major elements of many logistics systems, and a large amount of research has been devoted to find good solutions to these complex combinatorial optimization problems. The vehicle routing problem (VRP) is one of the major research topics, which involves finding a set of routes, starting and ending at depots, which together cover a set of customers. Each customer has a given demand, and no vehicle can service more customers than its capacity. The objective can be to minimize the total distance traveled or the number of vehicles used or combination of these objectives. Also, in the United States, the road toll system condition is standard, so this is simplifies the analysis of vehicle routing. The solution to the vehicle routing problem with time windows must ensure that the service of any customer starts within a given time interval, so it is called "time window". The most elementary version of the

vehicle routing problem is the capacitated vehicle routing problem (CVRP). An important extension of the CVRP is the vehicle routing problem with time windows (VRPTW) (Luca Maria Gambardella 2000). As we mentioned, the objective is to minimize the vehicle fleet and the sum of the travel time and waiting time needed to supply all customers in their required hours. The VRPTW has some restrictions. First, a solution becomes infeasible if a customer is supplied after the upper bound of its time window. Second of all, a vehicle arriving before the lower limit of the time window causes additional waiting time on the route. Third, each route must start and end with the time window associated with the depot. Finally, in the case of soft time windows, a later service does not affect the feasibility of the solution, but is penalized by adding a value to the objective function. In the Figure 3, blue and white bars are representing the time window (e.g. business hours), where the white area represents when make a delivery can be made to that customer. By other side, the red line shows when the delivery was made for this particular solution.

Figure 3 Instance for Solving With VRPTW
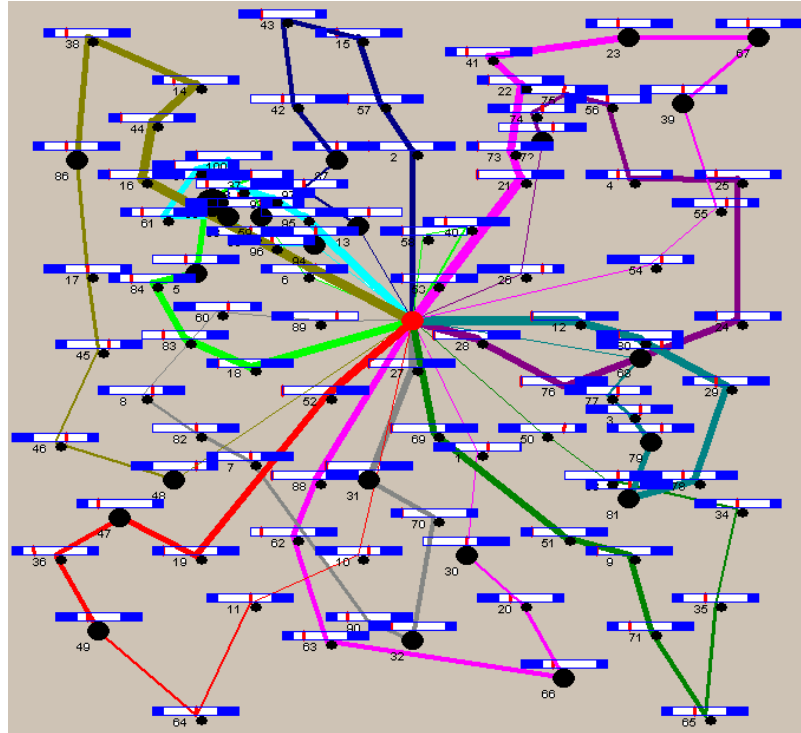
Figure 3 is screenshot of a vehicle routing software.

3.1.4 Some Other VRP Variants

3.1.4.1 Capacitated VRP (CVRP)

CVRP is a Vehicle Routing Problem (VRP) in which a fixed fleet of delivery vehicles of uniform capacity must service known customer demands for a single commodity from a common depot at minimum transit cost. That is, CVRP is similar to VRP with the additional constraint that every vehicle must have uniform capacity of a single commodity. The objective of CVRP is to minimize the vehicle fleet and the sum of travel time, and the total demand of commodities for each route may not exceed the capacity of the vehicle which serves that route. The feasible solution to CVRP occurs if the total quantity assigned to each route does not exceed the capacity of the vehicle which services the route.

3.1.4.2 Multiple Depots VRP (MDVRP)

A company may have several depots from which it can serve its customers. If the customers are clustered around depots, then the distribution problem should be modeled as a set of independent VRPs. However, if the customers and the depots are intermingled then a Multi Depot Vehicle Routing Problem should be solved.

A MDVRP requires the assignment of customers to depots. A fleet of vehicles is based at each depot. Each vehicle originates from one depot, services the customers assigned to that depot, and returns to the same depot. The objective of the MDVRP is to minimize the vehicle fleet and sum of travel time. The total demand of commodities must be served from several depots. The feasible solution of MDVRP would be to make each route satisfy the standard VRP constraints while beginning and ending at the same depot.

3.1.4.3 Periodic VRP (PVRP)

In classical VRPs, typically the planning period is a single day. In the case of Period Vehicle Routing Problem (PVRP), the classical VRP is generalized by extending the planning period to a certain days. The objective of PVRP is to minimize the vehicle fleet and the sum of travel time needed to supply goods to all customers. The feasible solution of PVRP is if all constraints of VRP are satisfied. Furthermore a vehicle may not return to the depot in the same day it departs. Over the certain day's period, each customer must be visited by trucks at least once.

3.1.4.4 Split Delivery VRP (SDVRP)

SDVRP is a relaxation of the VRP where it is allowed that the same customer can be served by different vehicles if it reduces overall costs. This relaxation is very important if

of the customer orders are many enough for the capacity of a vehicle. The objective of SDVRP is to minimize the vehicle fleet and the sum of travel time needed to supply goods to all customers. The SDVRP is solved when all constraints of VRP are satisfied. This solution is not feasible in a case where a customer may be supplied by more than one vehicle.

3.1.4.5 Stochastic VRP (SVRP)

Stochastic VRP (SVRP) is VRPs where one or several components of a problem are random. There are three different kinds of SVRP: stochastic customers, stochastic demands, and stochastic times. In SVRP, two stages are established for getting a solution. One solution can be made before the realizations of the random variables. The other is recourse or corrective action that can be taken when the values of the random variables are known. The objective of SVRP is to minimize the vehicle fleet and the sum of travel time needed to supply goods to all customers with random values on each execution of services for the customer demands, their demands and/or travel times.

3.1.4.6 VRP with Backhauls

The Vehicle Routing Problem with Backhauls (VRPB) is a VRP in which customers demand or return some commodities. So, in VRPPD it's needed to take into account that the goods that customers return to the delivery vehicle. The critical assumption that all deliveries must be made on each route before any pickups can be made. This assumption is based on the fact that the vehicles are rear-loaded, and rearrangement of the loads on the tracks at the delivery point is not deemed economical or feasible. The quantities of the goods to be delivered and picked-up should be fixed and known in advance. VRPB is

similar to VRPPD except the restriction that in the case of VRPB all deliveries for each route must be completed before any pickup is made.

3.1.4.7 VRP with Pick-Up and Delivering

The Vehicle Routing Problem with Pick-up and Delivering (VRPPD) is a VRP in which the possibility that customers return some commodities is contemplated. So in VRPPD it's needed to take into account that the goods that customers return to the delivery vehicle must fit into it. This restriction makes the problems related planning more difficult and can lead to problems: bad utilization of the vehicles capacities, increased travel distances or a need for more vehicles.

Hence, usually restricted situations should be considered, these situations include a case that all delivery demands start from the depot and all pick-up demands shall be brought back to the depot, so there are no interchanges of goods between the customers. Another problem can be relaxed of is relaxing of the restriction that each customer has to be visited by truck exactly once. Another usual simplification is the case when every vehicle must deliver all the commodities before picking up any goods. The objective of VRPPD is to minimize the vehicle fleet and the sum of travel time, with the restriction that the vehicle must have enough capacity for transporting the commodities to be delivered and those ones picked-up at customers for returning them to the depot. The feasible solution is that the total quantity assigned to each route does not exceed the capacity of the vehicle which supports services on the route and the vehicle has enough capacity for picking-up the commodities at customers.

3.2 Traditional Models of Vehicle Routing Problem with Time Windows

3.2.1 Overall VRP Optimization Algorithms

As we mentioned, most customers need their goods delivered to their place within a certain time. So, in this section, most of the algorithms are based on the "time windows" theory.

Vehicle routing problem with time window does not have a long history. The first paper on an optimization method for the VRPTW appeared as late as 1987. (Niklas Kohl et al. 1995) All of the algorithms are based on some mathematical theories.

3.2.2 Specific Algorithms

3.2.2.1 Lagrangian Relaxation

Lagrangian relaxation is a relaxation technique. This technique works by moving hard constraints into the objective and exacting a penalty on the objective if they are not satisfied as well.

Given a Linear Programming problem $x \in R^n$ and $A \in R^{m,n}$ of the following from.

$$\text{Max} \quad c^T x$$

$$\text{s.t. } Ax \le b$$

If we split the constraints in A such that $A_1 \in R^{m_1,n}$, $A_2 \in R^{m_2,n}$ and $m_1 + m_2 = m$ we may write the system as follow.

$$\text{Max} \quad c^T x$$

$$\text{s.t. } A_1 x \le b_1 (1)$$

$$A_2 x \le b_2 (2)$$

We may introduce the constraint $A_2 \leq b_2$ into the objective as follow.

$$\text{Max} \qquad c^T x + \lambda^T (b_2 - A_2 x)$$

$$\text{s.t. } A_1 x \leq b_1 \text{(1)}$$

If we let $\lambda = (\lambda_1, ..., \lambda_{m2})$ be nonnegative weights, we get penalty of objective if we violate the constraint $A_2 \leq b_2$. We are also rewarded if we satisfy the constraint strictly. The above system is called the Lagrangian Relaxation of our original problem.

With particular use if Lagrangian Relaxation, it is the property that for any fixed set of $\tilde{\lambda}$ values, the optimal result to the Lagrangian Relaxation problem is no smaller than the optimal result to the original problem. To see this, let $\hat{x}$ be the optimal solution to the original problem, and let $\bar{x}$ be the optimal solution to the Lagrangian Relaxation. We can then see that

$$c^T \hat{x} \leq c^T \hat{x} + \tilde{\lambda}^T (b_2 - A_2 \hat{x}) \leq c^T \bar{x} + \tilde{\lambda}^T (b_2 - A_2 \bar{x})$$

The first inequality is true because $\hat{x}$ is feasible in the original problem and the second inequality is true because $\bar{x}$ is the optimal solution to the Lagrangian Relaxation. This, in turn, allows us to address the original problem instead of exploring the partially dualized problem as follow.

$$\text{Min} \qquad P(\lambda)$$

$$\text{s.t. } \lambda \geq 0$$

where we define P(λ) as

$$\text{Max} \qquad c^T x + \lambda^T (b_2 - A_2 x)$$

$$\text{s.t. } A_1 x \leq b_1 \text{(1)}$$

A Lagrangian Relaxation algorithm thus proceeds to explore the range of feasible λ values while seeking to minimize the result returned by the inner P problem. Each value returned by P is a candidate upper bound to the problem, the smallest of which is kept as the best upper bound. If we additionally employ a heuristic, probably seeded by the $\bar{x}$ values returned by P, to find feasible solutions to the original problem, then we can iterate until the best upper bound and the cost of the best feasible solution converge to a desired tolerance.

3.2.2.2 Heuristics

In engineering, a heuristic is an experience-based method that can be used as an aid to solve process design problems, varying from size of equipment to operated conditions. By using heuristics, we can save some time when solving problems. There are several methods, which are available to engineers. These include Failure Mode and Effects Analysis and Fault Tree analysis. The first one relies on a group of qualified engineers to evaluate problems, rank them in order of importance and then recommend solutions. The methods of forensic engineering are important sources of information for investigating problems, especially by elimination of unlikely causes and using the weakest link principle. Because heuristics are fallible, it is important to understand their limitations. They are intended to be used as aids in order to make quick estimates and preliminary process designs.

Several families of heuristics have been proposed for the Vehicle Routing Problem (VRP). These can be broadly classified into two main classes. Classical heuristics was developed mostly between 1960 and 1990. The other is metaheuristics which grew in the

last decade. Most standard construction and improvement procedures in use today belong to the first class. These methods perform a relatively limited exploration of the search space and typically produce good quality solutions within modest computing times. Moreover, most of them can be easily extended to account for the diversity of constraints encountered in real-life contexts. Therefore, they are still widely used in commercial package. In metaheuristics, the emphasis is on performing a deep exploration of the most promising regions of the solution space. These methods typically combine sophisticated neighborhood search rules, memory structures, and recombination of solutions.

3.2.2.3 Savings Algorithm

Savings Algorithm of Clarke and Wright (1986) is one of the best approaches to solve the Vehicle Routing Problem (VRP).

The problem is given as follow. Let there be n demand points in a given area, each demanding a quantity of weight Q_i (i = 1, 2 . . . n) of goods to be delivered to it. The goods are stored at a depot, D, where a fleet of vehicles is also stationed. Vehicles have identical maximum weight capacities and maximum route time (or distance) constraints. They must all start and finish their routes at the depot, D. The problem is to obtain a set of delivery routes from the depot, D, to the various demand points to minimize the total distance covered by the entire fleet. It is assumed that the weights Q_i (i = i, . . . , n) of the quantities demanded are less than the maximum weight capacity of the vehicles and we require that the whole quantity Q_i demanded at a given point i be delivered by a single vehicle (i.e., we do not allow for the possibility that one third, say, of Q_i will be delivered by one vehicle and the remaining two thirds by another).

Suppose that initially the solution to the VRP consists of using n vehicles and dispatching one vehicle to each one of the n demand points. The total tour length of this solution is, obviously, 2*SUM (i=1 to n)[d(D,i)] where d(x,y) is the distance between x and y.

If, now, we use a single vehicle to serve two points, say i and j, on a single trip, the total distance traveled is reduced by $s_{(i,j)}$.

$$s_{(i,j)} = 2d(D,i) + 2d(D,j) - [d(D,i) + d(i,j) + d(D,j)] = d(D,i) + d(D,j) - d(i,j)$$

The quantity $s_{(i,j)}$ is known as the "savings" resulting from combining points i and j into a single tour. The larger $s_{(i,j)}$ is, the more desirable it becomes to combine i and j in a single tour. However, i and j cannot be combined if in doing so the resulting tour violates one or more of the constraints of the VRP.

The following is the savings algorithm.

1. Calculate the savings $s_{(i,j)} = d(D,i) + d(D,j) - d(i,j)$ for every pair (i, j) of demand points.

2. Rank the savings $s_{(i,j)}$ and list them in descending order of magnitude. This creates the "savings list." Process the savings list beginning with the topmost entry in the list (i.e. the largest $s_{(i,j)}$).

3. For the savings $s_{(i,j)}$ under consideration, include link (i,j) in a route if no route constraints will be violated through the inclusion of (i,j) in a route, and if:

a. Either, neither i nor j have already been assigned to a route, in which case a new route is initiated including both i and j.

b. Or, exactly one of the two points (i or j) has already been included in an existing route and that point is not interior to that route (a point is interior to a route if it is not adjacent to the depot D in the order of traversal of points), in which case the link (i,j) is added to that same route.

c. Or, both i and j have already been included in two different existing routes and neither point is interior to its route, in which case the two routes are merged.

4. If the savings list s $_{(i,j)}$ has not been exhausted, return to Step 3, processing the next entry in the list; otherwise, stop: the solution to the VRP consists of the routes created during Step 3. Any points that have not been assigned to a route during Step 3 must each be served by a vehicle route that begins at the depot D visits the unassigned point and returns to D.

The savings algorithm can be programmed to run very efficiently and, since it involves very simple manipulations of the data set, it can be used with large problems. Because nodes are added to routes one or two at a time, an additional advantage of the algorithm is that it is possible to check whether each addition would violate any set of constraints, even when that set is quite complicated. For instance, besides the constraints on maximum capacity and maximum distance, other constraints might be included, such as a maximum number of points that any vehicle may visit.

There is no guarantee that the solution provided by this algorithm will be anywhere close to the optimum. While experience has shown that the algorithm performs quite well most of the time, it is possible to devise "pathological" cases for which the Savings Algorithm solutions are very poor indeed. However, it is often possible to improve considerably, by inspection, a set of VRP tours produced by the savings algorithm.

3.2.2.4 Linear Programming

Operations management often presents complex problems that can be modeled by linear functions. The mathematical technique of linear programming is instrumental in solving a wide range of operations management problems. Linear programming model is not only

used for solving in truck routing problems but also use for solve other many aspects of business administration including in product mix planning, distribution networks, staff scheduling, financial portfolios, and corporate restructuring. The basic mathematics theory of linear programming relaxation and its applications is discussed here.

Linear programming models consist of an objective function and the constraints on that function. A linear programming model takes the following form.

Objective function:

$$Z = a_1X_1 + a_2X_2 + a3X_3 + \ldots + a_nXn$$

Constraints:

$$b_{11}X_1 + b_{12}X_2 + b_{13}X_3 + \ldots + b_{1n}Xn < c_1$$

$$b_{21}X_1 + b_{22}X_2 + b_{23}X_3 + \ldots + b_{2n}Xn < c_2$$

$$.$$

$$.$$

$$.$$

$$b_{m1}X_1 + b_{m2}X_2 + b_{m3}X_3 + \ldots + b_{mn}X_n < cm$$

In this system of linear equations, Z is the objective function value that is being optimized, X_i are the decision variables whose optimal values are to be found, and a_i, b_{ij}, and c_i are constants derived from the specifics of the problem.

Linear Programming formulations have certain assumptions. Linear programming requires linearity in the equations as shown in the above structure. In a linear equation, each decision variable is multiplied by a constant coefficient with no multiplying between decision variables and no nonlinear functions such as logarithms. Linearity requires the following assumptions:

- Proportionality - a change in a variable results in a proportionate change in that variable's contribution to the value of the function,
- Additively - the function value is the sum of the contributions of each term, and
- Divisibility - the decision variables can be divided into non-integer values, taking on fractional values. Integer programming techniques can be used if the divisibility assumption does not hold.

In addition to these linearity assumptions, linear programming assumes certainty; that is, that the coefficients are known and constant.

With computers software able to solve linear programming problems with ease, the challenge is in problem formulation - translating the problem statement into a system of linear equations to be solved by computer. The information required to write the objective function is derived from the problem statement. The problem is formulated from the problem statement as follows.

1. Identify the objective of the problem; that is, which quantity is to be optimized. For example, one may seek to maximize profit,

2. Identify the decision variables and the constraints on them. For example, production quantities and production limits may serve as decision variables and constraints, and

3. Write the objective function and constraints in terms of the decision variables, using information from the problem statement to determine the proper coefficient for each term. Discard any unnecessary information.

4. Add any implicit constraints, such as non-negative restrictions.

5. Arrange the system of equations in a consistent form suitable for solving by computer. For example, place all variables on the left side of their equations and list them in the order of their subscripts.

The following guidelines help to reduce the risk of errors in problem formulation:

•   Be sure to consider any initial conditions.

•   Make sure that each variable in the objective function appears at least once in the constraints.

•   Consider constraints that might not be specified explicitly. For example, if there are physical quantities that must be non-negative, then these constraints must be included in the formulation.

Constraints exist because certain limitations restrict the range of a variable's possible values. A constraint is considered to be binding if changing it also changes the optimal solution. Less severe constraints that do not affect the optimal solution are non-binding.

Tightening a binding constraint can only worsen the objective function value, and loosening a binding constraint can only improve the objective function value. As such, once an optimal solution is found, managers can seek to improve that solution by finding ways to relax binding constraints.

3.3 Using New Technology (Software) to Simulate The Vehicle Routing

3.3.1 Why Use Optimization Software to Solve Vehicle Routing Problems

In vehicle routing there are loads of goods or many people that need to be transported from one place to another, over a limited period of time. There are routes assigned to each vehicle and the dispatcher will communicate these in due time. Costs, time effectiveness and quality of services are only some of the many things a dispatching department has to consider and harmonize. While measure of cost and measure of level of services are generally considered as statistic design problems, problems such as sequential routing problems (routing a vehicle based on a time-line) are considered dynamic problems. All these issues are dealt with by professionals who help keep the wheels in motion at the right pace.

Vehicle dispatching carries an essential role in the managerial logistic function; if the freight is properly routed then the company can achieve both minimization of logistics cost and satisfaction of customer expectations and needs.

As soon as the contract is signed the provider has the obligation to dispatch goods to the beneficiary as soon as possible. Most companies choose to hire a carrier to take care of the logistics of the operation. The carrier is responsible for a number of activities such as loading and unloading of goods but its most important role is to safely and quickly

dispatch the loaded goods from expedition to destination. To do this dispatching department puts together a plan with the number of vehicles and the maximum load they can carry and defines a thorough road map for all vehicles. It is also in the department's job descriptions to verify and sustain accurate time-lines for each vehicle. All these details are carefully arranged so as to avoid delays (which automatically mean more costs for both the expediter and the carrier) and, most of all, congestion of vehicle on the roads or even worst in terminals. Both congestion and delays mean more costs for the client of the carrier (the supplier) because the supplier will have to pay penalties (as stipulated by INOTERMS) to the receiver of the goods. For the carrier, on the other hand, undelivered goods mean a high inventory, deposit-costs and automatically raise the problem of larger facility spaces. An optimal carrier company will have many trucks and vehicles that never stay parked in terminals and which barely ever leave for the same directions simultaneously.

Less troublesome, but even more important and vital than the commercial dispatching services are the public - social vehicle dispatching services. Without public dispatching of school buses, tourist buses, trains and other public transportation means or without correct routing of public facilities such as garbage trucks our lives would be a constant bedlam. To realize the importance of these services remember the last time a bus was late and you were trying to get to work on time or the last time a garbage truck was 3 hours late in picking the trash on a hot summer day. These vehicle routing services are offered free of charge by the public administration and they are paid for by the government of each country. In some regards they could be viewed as more complex and intricate operations than their commercial counterparts. While a carrier can refuse a client's

requests on grounds of overloading or lack of personnel, the public - services providers are not able to tell citizens their daily needs will not be met, that their children will not be dropped off at school or that the garbage will not picked up that day. It is a strenuous work of many individuals working as a team; a work with results that are generally appreciated when one feels their lack.

Whether it is public or private vehicle dispatching that you think of, it is order and harmony that you have in mind. A dispatcher is close to a leader - he is the one that sets the routs, calculates the time, sends out the instructions and verifies position of each pawn on the intricate road chess-board. Without his professional probility, his meticulous attention to details and dedication for his work our roads would be total anarchy and our lives a total chaos.

All this would be next-to-impossible without some tools aid the process. One of the most important tools in any dispatching operation whether there are 1 or 2 vehicles or hundreds, is the use of dispatch software. Dispatch software can save money by creating higher efficiencies in operation. Better scheduling and better information to dispatchers and drivers will also help improve your company customer service.

3.3.2 Examples of Routing Optimization Software

3.3.2.1 Fleet Route

Fleet Route is geographic information system-based modeling software for high density residential routing, point-to-point commercial/special waste routing, and districting/ analytics/area routing. It balances route times, service days and districts; optimizes travel

paths; and reduces the time and cost associated with updating routes. It also integrates with customer service and billing systems. Developed and regularly updated by waste industry veterans and leading GIS experts, Fleet Route™ represents nearly two decades' experience in designing, building and implementing route optimization software for local governments and the waste industry.

Fleet Route is flexible and completely customized for your specific requirements. It is available as software for in-house route management or as a service where routing is outsourced to GBB's service bureau.

3.3.2.2 Intelligent Routing

With more than 6,695,000 miles of truck attributed roads and 35% more commercial truck restrictions than other solutions, Intelligent Route™ is the transportation industry's leading truck routing product. Over 94% of the top freight carriers utilize Rand McNally software to optimize and enhance their operations with intelligent routing and accurate mileages. With Intelligent Route, software can use for minimize operating costs while maximizing on-time delivery.

The following are the key features and benefits of Intelligent Route:

- Truck-specific address-to-address routing for the United States and Canada,
- Avoid out-of-route (OOR) miles with accurate routing for truck specific, configurations and Haz Mat,
- Avoid accidents and tickets by using roads and bridges that accommodate truck height, weight and length,

- Superior Data – Intelligent Route contains 35% more truck restriction data than the leading data supplier,

- Save Money - Studies show that accurate optimized routing can reduce transportation expenses by up to 7%,

- Find the most cost effectiveness routes by using up-to-date Toll Cost information,

- Bypass Road Construction projects with Intelligent Route RoadWork - updated every 2 weeks, and

- Many features in one package - Tolls, Spreadsheets, Batch Processing, Road Construction & Free Quarterly Data Updates.

3.3.2.3 Direct Route

Direct Route helps companies to gain control and reduce cost. Companies spend large amounts of money controlling the flow of boxes in a warehouse and then release fleets and inventory to travel thousands of miles each week. Also, Direct Route helps companies optimize their transportation, generate accurate schedules, and gain control of their fleet operations to continue the chain of efficiency through to end customers.

Two decades of experience and over 1,000 client implementations are incorporated into the next generation fleet routing system that is truly in a category on its own. Direct Route™ V9 was built from the ground up to take advantage of .Net architecture, XML interfacing, and to expand on the tools and features built into the flagship product over the years.

Most systems created during the expansion of business PC's carry over programming code that was first introduced in DOS and was migrated to Windows. Simply revamping

old code does not allow a system to take advantage of new processing power and user-interface capabilities.

Chapter 4 Methods

4.1Rationale for Using The Method Chosen

This research will use two traditional models; there are Linear Programming, and saving heuristic algorithm. We do not use Lagrangian Relaxation, because it is not feasible to calculate by the normal software. It will spend the company too much time for waiting the software to run the data.

4.1.1 Linear Programming

Operations management often presents complex problems that can be modeled by linear functions using the mathematical technique. Linear programming model is not only in use for solving truck routing problems but also is used to solve many other aspects of

business administration included in product mix planning, distribution networks, staff scheduling, financial portfolios, and corporate restructuring. The basic mathematics theory of linear programming relaxation and its applications are discussed.

The function and constraints of Linear Programming were showed in the background. Based on the function and constraints, the Linear Programming's flowchart is showed in Figure 4.

Figure 4 Flowchart of Linear Programming
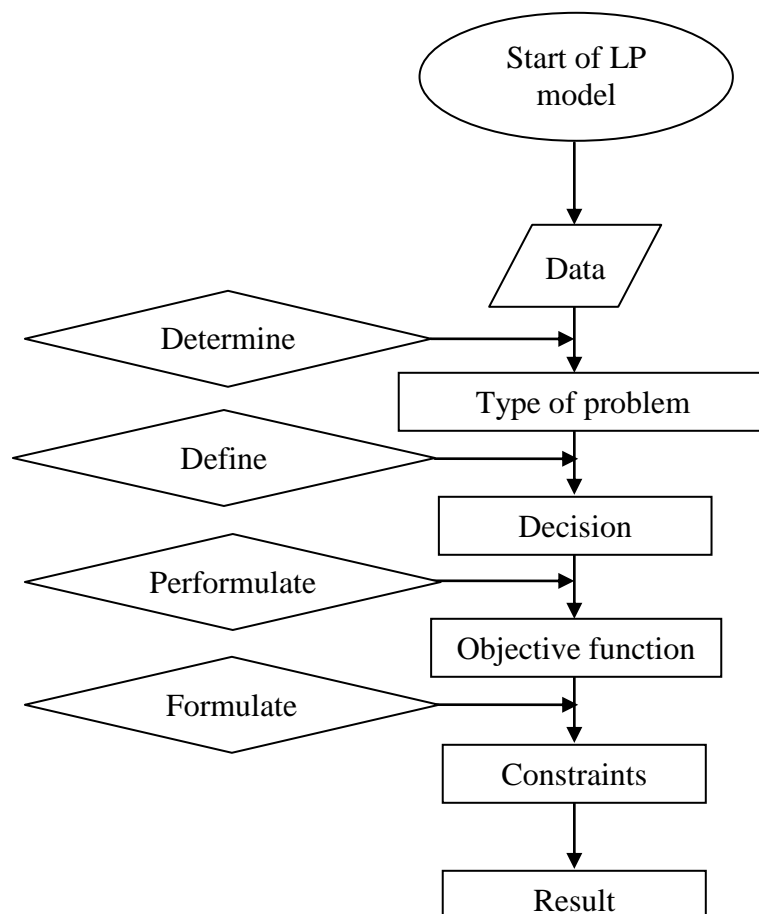
Figure 4 displays the process of Linear Programming method of vehicle routing problem.

4.1.2 Saving Heuristic Algorithm

The Clarke and Wright (1964) savings algorithm is perhaps the most widely known heuristic for the VRP. It can be applied to the problems for which the number of vehicles, is a decision variable and it works equally well for directed or undirected problems. This algorithm has two versions namely parallel and a sequential version. The algorithm works as follows.

Step 1 (Savings computation) The savings is calculated using the equation

$$s_{ij} = c_{i0} + c_{0j} - c_{ij} \qquad \text{for i, j} = 1, \dots, \text{n and i} = \text{j.}$$

where, s_{ij} is saving miles between two stores.

The c_{ij} contribution coefficients, which represent the per unit contribution of each unit of the decision variable to Z

The savings are calculated for n vehicle routes (0,i,0) for i = 1,...,n. And it is then arranged in a non- increasing fashion.

Step 2 (Parallel or Sequential version)

Parallel version (Best feasible merge) follows procedure is executed from the beginning of the above saving list, which has been arranged in a non – increasing fashion. For a given saving s_{ij}, determine whether two routes exists, one starting with (0,j), and the other one ending with (i, 0). And also check whether there is a possibility to merge the two routes if they exist. If so, combine these two routes by deleting (0, j) and (i, 0) and introducing (i, j).

Sequential version (Route extension) considers in turn each route (0, i. . . j, 0). Determine the first saving $S_{i,n}$ or $S_{n,j}$ that can feasibly be used to merge the current route with another route ending with (i, 0) or starting with (0, j). Implement the merge and repeat this operation to the current route. If no feasible merge exists, consider the next route and reapply the same operations. Stop when no route merge is feasible.

The flowchart is presented in Figure 5.

Figure 5 Flowchart of Saving Heuristic Algorithm
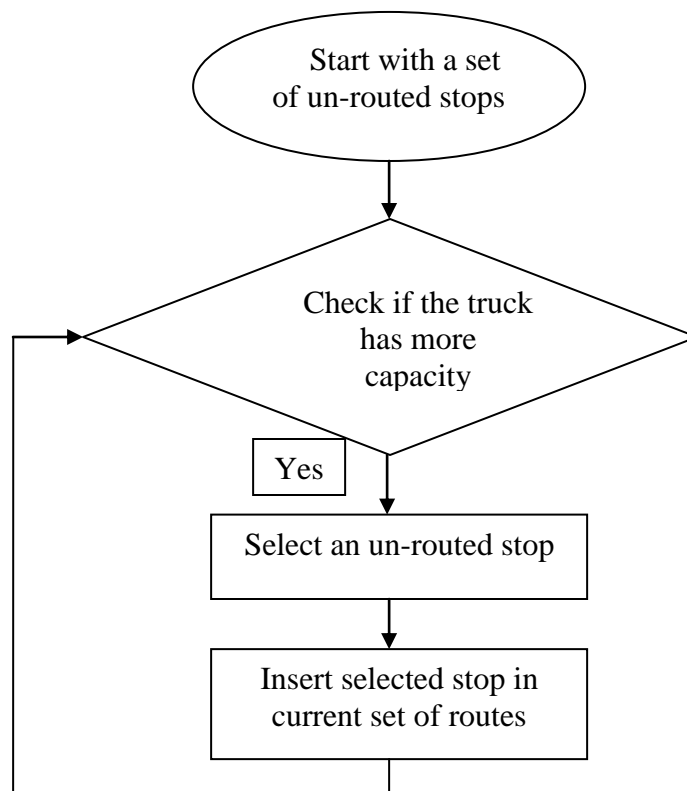
Figure 5 displays the process of saving heuristic algorithm for solving the vehicle routing problem.

4.2 Data Collection Procedure

The data is used in this research obtained from Wal-Mart. Wal-Mart' online stores finder function is used to obtain the entire Wal-Mart stores and their suppliers locations. The distances between stores and the suppliers are calculated in miles using the software PC*MILER. This software is the routing, mileage and mapping software that the transportation and logistics industry depends on. The software has the entire North America road database. It is compatible with Microsoft excel, which enables the exporting the data to excel easier allowing to do for further calculations. The demand of the data is simulated based on the population of the cities.

4.3 Analysis Plan

Test and Confidence Level

Sensitivity analysis (SA) is the study of how the variation (uncertainty) in the output of a mathematical model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of the model (Saltelli, et.al 2008). In other words, it is a technique for systematically changing parameters in a model to determine the effects of such changes.

In more general terms uncertainty and sensitivity analysis investigate the robustness of a study when the study includes some form of mathematical modelling. Also, the sensitivity analysis can be useful to computer modellers for a range of purposes as well. (Pannell, D.J. 1997)

The best model is identified by the smaller rate of change when a parameter is changed. According to the research (AAA report , 2010) that the stores in the Nebraska area, one of the high frequency changing parameter is truck oil price, and the range of the oil price change is $\pm 13.7\%$ in the past year. Therefore, in the sensitivity analysis, we will let the oil price changes in $\pm 13.7\%$ and see the change rate of the final result in each model. According to the calculation, with the increasing of the oil price up to 13.7%, the total cost of LP is increased 0.3%, the saving algorithm is increased 0.34%, and the Direct Route is increased 2%. As we know, the best model is the most insensitivity model. So the Direct Route is the best model of the three models.

In this research, the parameters considered for calculating of the basic cost are truck cost and labor cost. The basic cost can also be varied by some uncertain reasons in the different states in United States. The truck cost is varied based on the mileage, speed limits in different states, etc. This indicates the basic cost calculated using this model may be valid in one state, but vary in other states depending on the demand of customer, unit labor cost, unit fuel cost, etc. The rate of the basic cost changes due to the factors are mentioned above in different models.

4.4 Formula

4.4.1 Linear Programming (LP)

The mathematical model can be expressed as followed.

The objective function:

$$\min imizeZ = \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} \qquad (1)$$

Where Z is the objective function,

x_{ij} is the decision variable, which means the number of units shipped from supply center i to demand center j, and they are what we are going to find out to be an optimal value through LP.

c_{ij} is contribution coefficients, which represent the per unit contribution of each unit of the decision variable to Z.

In a transportation problem, c_{ij} could be the transportation cost for cargo in unit weight. The sum above adds up the cost for each route and gives the total transportation cost Z.

$$\sum_{j=1}^{n} x_{ij} = a_{i,(i=1,2,...,m)} \qquad (2)$$

$$\sum_{i=1}^{m} x_{ij} = b_{i,(j=1,2,...,n)} \qquad (3)$$

The total amount shipped out of supply center i is $\sum_{j}^{n} x_{ij}$ and the total amount arrived at

the demand center j is $\sum_{j}^{m} x_{ij}$. a_i and b_j are right-hand-side values and they are constraints

to the each ship. The technology coefficients are all set to be '1', which are moved from

the constraints.

As the total demand equals the total supply available,

$$\sum_{j=1}^{n} b_j = \sum_{i}^{m} a_i \qquad (4)$$

What should be pointed out is that the equation (4) is not a constraint to this problem but

is an assumption for this case. The non-negativity requirement is given as: $x_{ij} \geq 0$,

showing that this model requires all decision variables to be positive value or zero.

There are some special properties for transportation problems, such as if the data of the

problem is integral, then the solution to the problem will be integral as well. Every

variable appears in two constraint functions. It must have an optimal solution for this type

of transportation problems. Since the shipping units cannot be in negative integers, we

can assume that the variables x_{ij} take on non-negative integer. That means we can only

ship items in whole number batches. For example, an integrated machine or a living

animal can't be shipped in fractional number.

Our case is optimizing the vehicle routing problem of 18 Wal-Mart stores. In this case,

the data is we think about there are one distribution center in North Platte (69101), and

two sub-DCs in Lincoln (68521) and Omaha (68137). And Each DC ships goods for their

region. The three regions are base on the geographical distribution. Stores in the each

region are shows in the Table 4.

Table 1 Stores Number in Each Region

Stores						
FROM\TO	Beatrice	Bellevue	Columbus	Crete	Fairbury	Fremont
Lincoln	50.1	62	73.5	28.5	72.9	50.1
Omaha	87.8	17.5	80.2	71	115	31.3
T Demand	2.2	7.9	3.7	1.1	0.8	4.5

Table 2 Stores Number in Each Region

Stores						
FROM\TO	Lincoln	Lincoln	NE City	Norfolk	Omaha	Omaha
Lincoln	-	13.2	56.4	119	58.5	45.4
Omaha	45	54.5	48.9	107	16	5.6
T Demand	20.0	20.0	1.3	4.2	17.3	17.3

Table 3 Stores Number in Each Region

Stores						
FROM\TO	Omaha	Omaha	Papillion	Seward	S Sioux	York
Lincoln	56.3	44.4	48.7	22.2	123	52.6
Omaha	9.3	-	12.1	64.9	106	95.1
T Demand	17.3	17.3	2.9	1.1	2.1	1.4

Applying stepwise procedure to the example in this work, we can first determine that this

transportation problem is about the cost. Therefore, this is a minimization problem. By

using LP method, we can easily find the number of the decision variables is 2*18=36, which are defined to be x_{l1} to xo_{18}.

The objective function is:

$$
\begin{aligned}
\min.z = & \; 50.1x_{l1} + 62x_{l2} + 73.5x_{l3} + 28.5x_{l4} + 72.9x_{l5} + 50.1x_{l6} \\
& + 13.2x_{l8} + 56.4x_{l9} + 119x_{l10} + 58.5x_{l11} + 45.5x_{l12} + 56.3x_{l13} + 44.4x_{l14} \\
& + 48.7x_{l15} + 22.2x_{l16} + 123x_{l17} + 52.6x_{l18} + 87.8x_{o1} + 17.5x_{o2} + 80.2x_{o3} \\
& + 71x_{o4} + 115x_{o5} + 31.3x_{o6} + 45x_{o7} + 54.5x_{o8} + 48.9x_{o9} + 107x_{o10} + 16x_{o11} \\
& + 5.6x_{o12} + 9.3x_{o13} + 12.1x_{o15} + 64.9x_{o16} + 106x_{o17} + 95.1x_{o18}
\end{aligned} \quad (5)
$$

where, $x_{l1} \ldots x_{l18}$ is sub-supply center in Lincoln to each 18 store

$x_{o1} \ldots x_{o1\,18}$ is sub-supply center in Omaha to each 18 store.

There have 20 constraints for this problem, which are listed as follows.

$$ x_{l1} + x_{l2} + x_{l3} + x_{l4} + x_{l5} + \ldots + x_{l18} = 72.3 \quad (6) $$

$$ x_{o1} + x_{o2} + x_{o3} + x_{o4} + x_{o5} + \ldots + x_{o18} = 70 \quad (7) $$

$$ x_{l1} + x_{l2} + x_{l3} + x_{l4} + x_{l5} + \ldots + x_{l18} = 72.3 \quad (8) $$

$$ x_{o1} + x_{o2} + x_{o3} + x_{o4} + x_{o5} + \ldots + x_{o18} = 70 \quad (9) $$

$$ x_{l1} + x_{o1} = 2.2 \quad (10) $$

$$ x_{l2} + x_{o2} = 7.9 \quad (11) $$

$$ x_{l3} + x_{o3} = 3.7 \quad (12) $$

$$ x_{l4} + x_{o4} = 1.1 \quad (13) $$

$$x_{l5} + x_{o5} = 0.8 \qquad (14)$$

$$x_{l6} + x_{o6} = 4.5 \qquad (15)$$

$$x_{l7} + x_{o7} = 20.0 \qquad (16)$$

$$x_{l8} + x_{o8} = 20.0 \qquad (17)$$

$$x_{l9} + x_{o9} = 1.3 \qquad (18)$$

$$x_{l10} + x_{o10} = 4.2 \qquad (19)$$

$$x_{l11} + x_{o11} = 17.3 \qquad (20)$$

$$x_{l12} + x_{o12} = 17.3 \qquad (21)$$

$$x_{l13} + x_{o13} = 17.3 \qquad (22)$$

$$x_{l14} + x_{o14} = 17.3 \qquad (23)$$

$$x_{l15} + x_{o15} = 2.9 \qquad (24)$$

$$x_{l16} + x_{o16} = 1.1 \qquad (25)$$

$$x_{l17} + x_{o17} = 2.1 \qquad (26)$$

$$x_{l18} + x_{o18} = 1.4 \qquad (27)$$

To solve the transportation problem by LP, the method is most commonly used to find out the optimal solution, which is embedded in the AB: QM computer software to be

applied in this work. When we use AB: QM, the input has been changed to x_i instead of x_{ij}, which expressions the difference with no change to the meaning of the variables.

4.4.2 Saving Heuristic Algorithm

The saving algorithm process is as follow:

1. Begin with n dedicated routes (round trips that service only one store), one for each of the n stores,

2. Compute savings in distance, S_{ij}, of combining every possible pair of stores1:

$$S_{ij} = d_{0i} + d_{0j} - d_{ij},$$

3. In a list, order the savings in a decreasing fashion. Since negative S values are obviously undesirable, omit the negative values from the list,

4. Build a route by adding pairs that do not violate any of the set constraints (truck volume or weight, etc...) in the order that they appear in the list until the route is full or the list has been exhausted. The resulting suppliers form a cluster, and

5. Repeat Step 4 until all stores are routed or the list has been exhausted.

The nomenclature and models are seen below.

The parameters are

m = miles,

$i =$ unit fuel cost,

s_i = service time at customer i,

$c_l =$ unit labor cost, and

$t_i =$ total time for i to j.

The variables are

C_L = Labor cost,

C_T = Truck cost, and

C_{TT} = Total cost.

The models are given below.

$$C_L = c_l * s_i \tag{28}$$

$$C_T = i * t_i \tag{29}$$

$$C_{TT} = C_L + C_T \tag{30}$$

The C_L is total labor cost. The C_T is total truck cost which the fuel cost of the total mileage of a route. The C_{TT} is total cost which including in total labor cost and total truck cost.

4.5 Demonstrate Model And Equation Develop Process With A Flowchart

Figure 6 Model and Equation Develop Process Flowchart
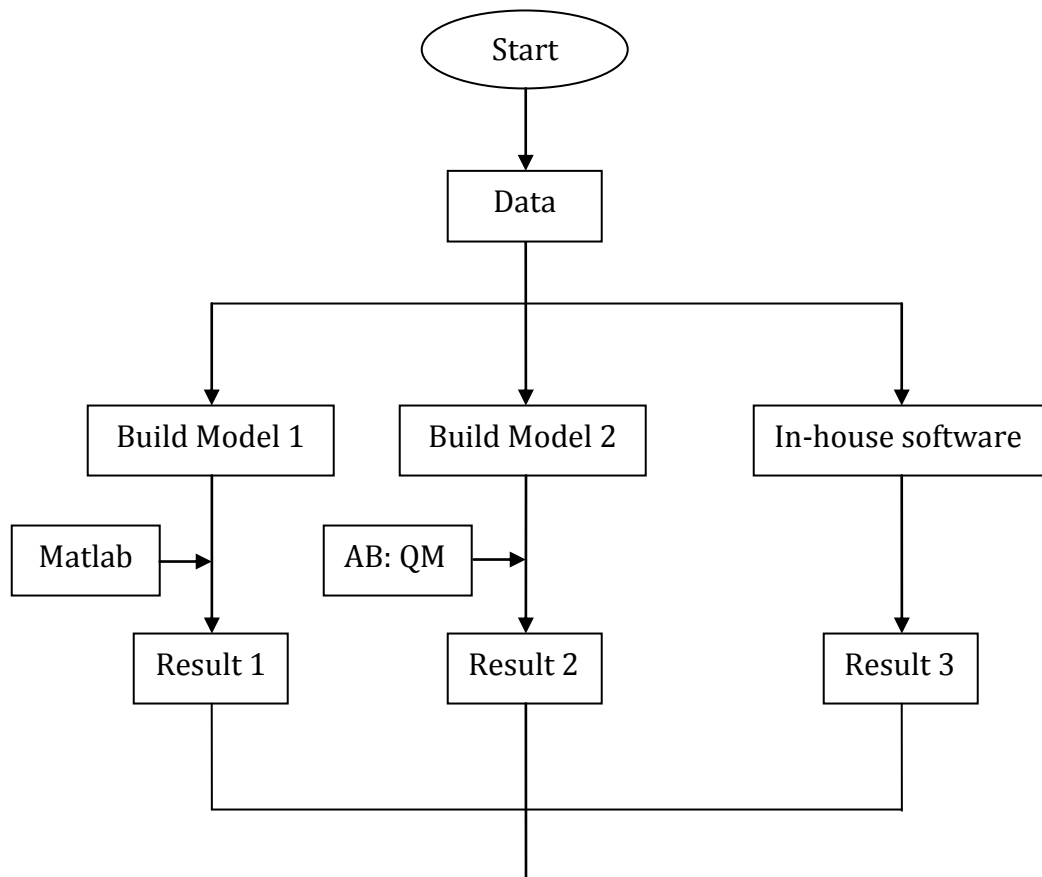
Figure 6 displays the process of this research. The method of this research uses the same data, in three different models. The three results were compared and find the best model was found.

4.6 A Demonstrated Sample Calculation and Procedure

In this section, each method is presented, and in order to make the procedure more obvious and simple, a small sample of data with the step-by-step way to present the process is given.

4.6.1 Linear Programming

In this part, we present two supercenters to two stores shipping condition. The data shows as follows.

Table 4 Sample Data of LP

Stores FROM\TO	Beatrice	Bellevue	Total supply

Lincoln	50.1	62	6
Omaha	87.8	17.5	5.1
Total Demand	2.2	7.9	10.1

Five steps procedures for formulating an LP model can be applied again to formulate an LP formulation of a transportation problem/model. Those steps are:

1. Determine the type of problem. The problem has to make clear that we are dealing with cost. The company's cost accountant estimates that it costs an average of $1 per mile, per unit to ship the units between the manufacturing plants and the warehouses. So it has to be a minimization.

2. Define the decision variables. The resulting four decision variables (i.e., 2 rows by 2 columns) can be defined as:

x_{11} = number of units to ship from Lincoln to Beatrice,

x_{12} = number of units to ship from Lincoln to Bellevue,

x_{21} = number of units to ship from Omaha to Beatrice, and

x_{22} = number of units to ship from Omaha to Beatrice.

3. Formulate the objective function: The formulation of the objective function follows easily from Steps 1 and 2. It is:

$$Z = 50.1x_{11} + 62x_{12} + 87.8x_{21} + 17.5x_{22}.$$

4. Formulate the constraints. The constraints are in two types: 2 supply constraints and 2 demand constraints as follows:

$$x_{11} + x_{12} = 6 \text{ (Lincoln supply constraint)},$$

$$x_{21} + x_{22} = 5.1 \text{ (Omaha supply constraint)},$$

$$x_{11} + x_{21} = 2.2 \text{ (Beatrice demand constraint)}, \text{ and}$$
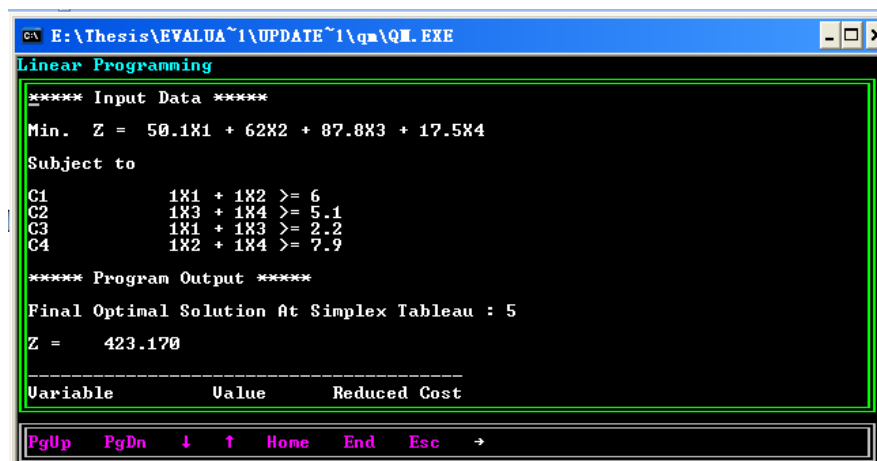
$$x_{12} + x_{22} = 7.9 \text{ (Bellevue demand constraint)}.$$

5. State the non-negativity and given requirements. All four decision variables must be the integer values of the units to be shipped. We can generally express the non-negativity and given requirements as:

$$x_{ij} > 0 \text{ and all integer}.$$

For this case, we use AB: QM software to run the data, the output result is in the Figure 7.

Figure 7 Result of Demonstrate of LP

Figure 7 displays the output results of demonstration of linear programming by AB: QM. We can see the minimum cost Z is \$423.17.

4.6.2 Saving Heuristic Algorithm

In this part, we present three stores as an example to explain the saving heuristic method.

Three stores zip code are 68310, 68310, 69337, and Distribution center zip code is 69101.

Which from this information,

We can get a miles matrix: miles matrix with the distances between each pair of stores.

The matrix is present as follow,

$$
\begin{pmatrix}
S_{11} & S_{12} & S_{13} \\
S_{21} & S_{22} & S_{23} \\
S_{31} & S_{32} & S_{33}
\end{pmatrix}
\tag{31}
$$

We have each store zip code, using PC*Miler; we can get the real miles of each pair of

stores.

$$
\begin{pmatrix}
0 & 105 & 486 \\
105 & 0 & 499 \\
486 & 105 & 0
\end{pmatrix}
\tag{32}
$$

The saving mile $(S_{ij}) = d_{0i} + d_{0j} - d_{ij}$, this formula showing us the distance between DC to

each store is needed. So the saving miles matrix is showing as follow.

$$
\begin{pmatrix}
0 & 456 & 12 \\
456 & 0 & 68 \\
12 & 0 & 0
\end{pmatrix}
\tag{33}
$$

The rank of miles-saving is given equation (34)

$$\begin{pmatrix} s_{12} \\ s_{23} \\ s_{13} \end{pmatrix} \tag{34}$$

The next step is adding capacity with demand constraint into the truck and finding the route.

This section is the main part of saving method. The capacity of the truck is 20 ton. The demand of these three is required. The demand data is showing as follow:

Demand for each store is:

$$demand = \begin{pmatrix} s_1 \\ s_2 \\ s_3 \end{pmatrix} = \begin{pmatrix} 2.22 \\ 7.87 \\ 0.99 \end{pmatrix} \tag{35}$$

From Step 3 we can see join store 1 and store 2 in a route first and see if the capacity of the truck is enough for the store demand. Demand for store 1 and store 2 are less than one truck's capacity. So store 1 and store 2 are in the same route. Then we should consider saving miles next. We can add store 3 in the same route, because the total demand is still less than the truck capacity. So the route should be: store 1, store 2, store 3 in the same route.

From the Matlab we can get the rank of saving mileage is:

$$S_{i,j} = \begin{pmatrix} 456 \\ 68 \\ 12 \end{pmatrix} \tag{36}$$

From equation (35) we can see the total demand of these three stores is 11.08 tons, which is less than truck capacity. The shipping sequence is:

$$DC \rightarrow store1 \rightarrow store2 \rightarrow store3 \rightarrow DC \tag{37}$$

So, based on the equation (28), (29), (30), the total cost of this route is $1402.

Chapter 5 Computational Results

In this chapter, all the models are from Chapter 4. The data is the whole sample. The same data was used in each model with different software. The results are shown as follow:

5.1 Linear Programming

Linear Programming model is the simplest one. The software we use is called AB: QM (Allyn and Bacon quantitative method). This software is designed by the College of Business Administration department in University of Nebraska- Lincoln. It is widely used in managerial decision-making processes. By the software, we can get to result of the two sub-supply centers' minimum cost is $2418.33 per miles*ton, plus the North Platte region cost $890.2, and the cost of North Platte shipping to sub-supply center $5406.35.The total cost we get is $8714.98.

Figure 8 Minimization Function of LP Model


```
C:\DOCUME~1\JIANHA~1\桌面\qm\QM.EXE                          - □ x
Linear Programming

***** Input Data *****

Min.  Z =  50.1X1 + 62X2 + 73.5X3 + 28.5X4 + 72.9X5 + 50.1X6 + 13.2X8
        + 56.4X9 + 119X10 + 58.5X11 + 45.5X12 + 56.3X13 + 44.4X14
        + 48.7X15 + 22.2X16 + 123X17 + 52.6X18 + 87.8X19 + 17.5X20
        + 80.2X21 + 71X22 + 115X23 + 31.3X24 + 45X25 + 54.5X26 + 48.9X27
        + 107X28 + 16X29 + 5.6X30 + 9.3X31 + 12.1X33 + 64.9X34 + 106X35
        + 95.1X36

Subject to

C1          1X1 + 1X2 + 1X3 + 1X4 + 1X5 + 1X6 + 1X7 + 1X8 + 1X9 + 1X10
     + 1X11 + 1X12 + 1X13 + 1X14 + 1X15 + 1X16 + 1X17 + 1X18 >= 72.3
C2          1X19 + 1X20 + 1X21 + 1X22 + 1X23 + 1X24 + 1X25 + 1X26
     + 1X27 + 1X28 + 1X29 + 1X30 + 1X31 + 1X32 + 1X33 + 1X34 + 1X35
     + 1X36 >= 70
C3          1X1 + 1X19 >= 2.2
C4          1X2 + 1X20 >= 7.9
C5          1X3 + 1X21 >= 3.7

PgUp    PgDn   ↓   ↑   Home    End    Esc    →
```

Figure 8 displays the objective functions of minimum cost of linear programming model.

The coefficients of the variables x_1, x_2, x_3 … x_{35} are unit cost of the truck on the road.

Under subject to c_1 and c_2 are supply constraints. c_3, c_4, c_5 … c_{18} are demand constraints.

Figure 9 Demand Constraints


```
C:\DOCUME~1\JIANHA~1\桌面\qm\QM.EXE                          - □ x
Linear Programming

C3          1X1 + 1X19 >= 2.2
C4          1X2 + 1X20 >= 7.9
C5          1X3 + 1X21 >= 3.7
C6          1X4 + 1X22 >= 1.1
C7          1X5 + 1X23 >= 0.8
C8          1X6 + 1X24 >= 4.5
C9          1X7 + 1X25 >= 20.0
C10         1X8 + 1X26 >= 20.0
C11         1X9 + 1X27 >= 1.3
C12         1X10 + 1X28 >= 4.2
C13         1X11 + 1X29 >= 17.3
C14         1X12 + 1X30 >= 17.3
C15         1X13 + 1X31 >= 17.3
C16         1X14 + 1X32 >= 17.3
C17         1X15 + 1X33 >= 2.9
C18         1X16 + 1X34 >= 1.1
C19         1X17 + 1X35 >= 2.1
C20         1X18 + 1X36 >= 1.4

PgUp    PgDn   ↓   ↑   Home    End    Esc    →
```

Figure 9 displays the demand constraints of each store of the linear programming model.

5.2 Saving Heuristic Algorithm

The saving algorithm process is steps are given below.

Step 1. Begin with n dedicated routes (round trips that service only one store), one for each of the n stores.

Table 5 shows us the matrix of savings and miles, but the matrix is not very clear. So we try to find another way to show the same kind of data in the next two types.

Table 5 Saving of Miles Matrix:

savings/miles	1	2	3	4	…	28
1	0	456	12	370	…	372.4
2	0	0	68	406.3	…	372
3	0	0	0	76	…	12
4	0	0	0	0	…	355
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
28	0	0	0	0	…	0

Step 2. Compute savings in distance, S_{ij}, of combining every possible pair of stores1: $S_{ij} = d_{0i} + d_{0j} - d_{ij}$

Step 3. In a list, order the savings in a decreasing fashion. Since negative S values are obviously undesirable, omit the negative values from the list.

Table 6 shows us the rank of the result of saving miles. In this table we just show a part

of data, the S_{ij} original data should be from the biggest to 0 from left to right.

Table 6 Rank of Result of Savings (S_{ij})

Rank of saving									
S_{ij}	565.3	542.3	529.4	520.7	514.3	513.8	510	503.2	500.7
I	2	2	16	16	16	16	16	2	19
J	23	16	23	19	21	20	22	7	27

Step 4. Build a route by adding pairs that do not violate any of the set constraints (truck

volume or weight, etc...) in order that they appear in the list until the route is full or the

list has been exhausted. The resulting suppliers form a cluster.

Step 5. Repeat Step 4 until all stores are routed or the list has been exhausted.

Table 7 Result of Routing

Routing in miles					
Route/vehicle Stores					
1	2	7	16		
2	4	8	9	23	
3	1	5	6	17	11	15
4	3	18	24	10	
5	21	25	28	26	
6	12	20			
7	19	27			
8	13				

| 9 | 14 |
| 10 | 22 |

Then based on the equation (28) (29) (30) we can calculate the total cost for each route.

The total cost for each route is shown in Table 8.

Table 8 Stores in Each Route of Saving Heuristic

Routes Truck							Total cost
1	2	7	16	23			1271.69
2	4	8	9	17			840.17
3	1	5	6	10	11	15	882.84
4	3	18	24	26			1089.02
5	21	25	28				748.92
6	12	20					720.25
7	19	27					930.49
8	13						597.59
9	14						618.53
10	25						710.17

Table 8 displays the result of the route by saving heuristic. In the last column is each route's total cost. Sum of the total cost for each route is the total of the whole 28 stores. The total cost is $8409.67.

5. 3 Direct Route Results

Direct Route has more restrictions than the two traditional models. The truck weight capacity is 20 tons trailers. The rules of the service time follow to the standard hour- of-service (HOS). Stores were split a max of 1 time. The fix time in each store is 30 minutes. Fix time at live load inbound was 120 minutes, and drop and hook inbound was 60 minutes. A stop must be 85% unloaded by the end of the delivery window. The scenarios were run outbound only. Before use Direct Route the data, we need to create a "stop file" and "truck file". The stop file includes the stops' (Customers) information, while the truck file includes fleet's (vehicle and distribution center) information.

Figure 10 A Part of Direct Route Stop File Data Sheet

	A	B	C	D	E	F	G	H	I	J
1	Store	City	State	Zip	Fixed Tim	Rt	Seq	Longitude	Latitude	Symbol
2	1	Beatrice	NE	68310	30	8	3	-96.7197	40.26806	Diamond
3	2	Bellevue	NE	68123	30	1	3	-95.9439	41.12306	Diamond
4	3	Chadron	NE	69337	30	12	3	-102.999	42.82944	Diamond
5	4	Columbus	NE	68601	30	3	1	-97.3656	41.43778	Diamond
6	5	Crete	NE	68333	30	3	2	-96.9386	40.62778	Diamond
7	6	Fairbury	NE	68352	30	8	4	-97.1528	40.13722	Diamond
8	7	Fremont	NE	68025	30	3	3	-96.4686	41.43333	Diamond
9	8	Grand Isl	NE	68801	30	8	1	-98.3486	40.92889	Diamond
10	9	Grand Isl	NE	68803	30	8	2	-98.3158	40.92444	Diamond
11	10	Hastings	NE	68901	30	8	5	-98.3761	40.56889	Diamond
12	11	Kearney	NE	68847	30	8	6	-99.0542	40.70111	Diamond
13	12	Lexington	NE	68850	30	6	1	-99.7253	40.78083	Diamond
14	13	Lincoln	NE	68521	30	10	1	-96.7136	40.83306	Diamond
15	14	Lincoln	NE	68526	30	9	1	-96.6953	40.88167	Diamond
16	15	Mccook	NE	69001	30	2	1	-100.605	40.205	Diamond
17	16	Nebraska	NE	68410	30	1	4	-95.8356	40.67694	Diamond
18	17	Norfolk	NE	68701	30	3	4	-97.4083	42.02917	Diamond
19	18	North Pla	NE	69101	30	1	1	-100.746	41.13722	Diamond

Figure 10 displays a part of stop file data. In the stop file, except for the data that showed in Figure 10, and also, it includes the time window for trucks.

Figure 11 A Part of Direct Route Truck Data Sheet

	A	B	C	D	E	F	G	H	I	J	K
1	TrkID	Available	OneWay	Redispatc	Weight	MiCost	HrCost	EarStart	EDate	LatStart	LatFinishl
2	1	TRUE	FALSE	FALSE	20	1	17	530	1		2359
3	2	TRUE	FALSE	FALSE	20	1	17	530	1		2359
4	3	TRUE	FALSE	FALSE	20	1	17	530	1		2359
5	4	TRUE	FALSE	FALSE	20	1	17	530	1		2359
6	5	TRUE	FALSE	FALSE	20	1	17	530	1		2359
7	6	TRUE	FALSE	FALSE	20	1	17	530	1		2359
8	7	TRUE	FALSE	FALSE	20	1	17	530	1		2359
9	8	TRUE	FALSE	FALSE	20	1	17	530	1		2359
10	9	TRUE	FALSE	FALSE	20	1	17	530	1		2359
11	10	TRUE	FALSE	FALSE	20	1	17	530	1		2359
12	11	TRUE	FALSE	FALSE	20	1	17	530	1		2359
13	12	TRUE	FALSE	FALSE	20	1	17	530	1		2359
14	13	TRUE	FALSE	FALSE	20	1	17	530	1		2359
15	14	TRUE	FALSE	FALSE	20	1	17	530	1		2359
16	15	TRUE	FALSE	FALSE	20	1	17	530	1		2359
17	16	TRUE	FALSE	FALSE	20	1	17	530	1		2359
18	17	TRUE	FALSE	FALSE	20	1	17	530	1		2359
19	18	TRUE	FALSE	FALSE	20	1	17	530	1		2359

Figure 11 displays a part of truck file data. In the truck file, except for the data showed in the figure, and also, it includes the max drive time, max work time, distribution center, and distribution's latitude and longitude.
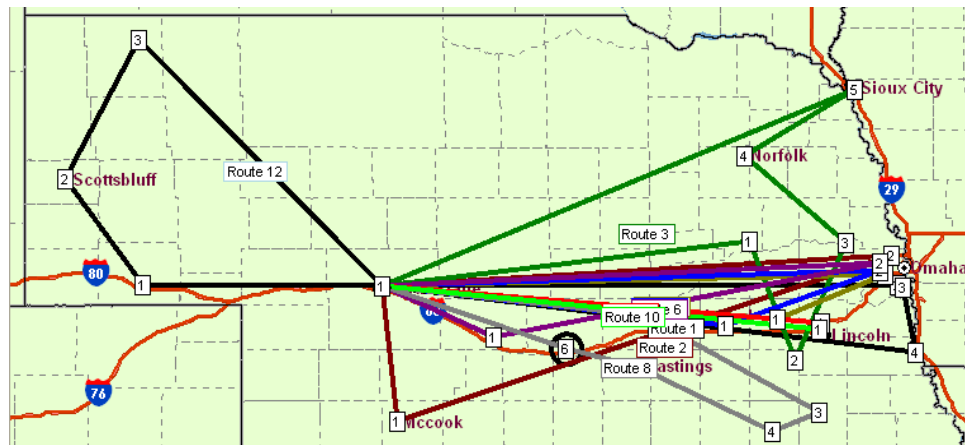
Figure 12 Result of Routing on Direct Route Map

Figure 12 displays the routing on Nebraska State's map. On the map we can see the total routes is 10 and all 28 stores are one the routes. The stores on each route are shown in Table 9

Table 9 Stores in Each Route of Direct Route

Routes Truck	Stores						Cost
1	2	23	16	18			904.31
2	15	19					927.6
3	4	5	7	17	27		1114.3
4	25	20					814.73
5	28	21					808.17
6	12	22					812.36
7	8	9	1	6	10	11	773.31
8	13						707.19
9	14						705.37
10	26	24	3				698.2

Table 9 displays the result the route by Direct Route. In the last column is each route total cost. The sum of the total cost for each route is the total of the whole 28 stores. The total cost is $8265.54.

Table 10 Result of Direct Route

Direct Route Result						
	Truck	*Tot Cost*	Tol Miles	Tol Hours	Total Stops	Avg Stops/ Truck
Total	10	8265.54	6318.2	114.54	28	2.8

In Table 10, truck is the size of the fleet of the specific type driver model time period (typically 1 week). From the table, total cost is $8265.54 by using in-house optimization software. The Direct Route has another useful function that it can show us the capacity rate for each route. We can use capacity rate to see the rate of utilization of the trucks visually, and then move some stops to low rate of utilization trucks, in order to reduce the total cost. It is shown as follows.

Table 11 Capacity Rate for Each Route

Capacity Rate										
Route	1	2	3	4	5	6	7	8	9	10
Capacity	81%	94%	78%	92%	94%	95%	99%	100%	100%	43%

From the results, the in-house transportation vehicle routing optimization software got the best result. It is not hard to say the reason. That is, compared with the two traditional models and in-house VRP software, and also, we can see that there are too many assumptions in the traditional models. Sometimes, we cannot setup the constraints too close or too wide. But the in-house optimization software gives the real constraints and many details to support the model. Also, the in-house optimization software is more adapted to real life situations. Moreover, the two traditional models, linear programming and saving algorithm have some disadvantages, and these disadvantages could lead the models' result to be a little different from real life situation. For example, linear programming has no correlation among variables and no positive or negative synergies. Those two disadvantages lead the model to loose or wide constraints. If the case is nonlinear programming, it is very difficult to use linear programming to solve it. For saving algorithm, as we have already mentioned, there is a disadvantage in the background. There is no guarantee that the solution provided by this algorithm will be anywhere close to the optimum. For Direct Route software, we can't assure that it can optimize every project perfectly. It may have some bugs that cannot be found. But compared to those two traditional models, Direct Route software is the best one. For the Direct Route customer shows that the software average mileage saving in industry is 10% - 25%; the hourly saving is 10% - 25%; and the truck saving is 7% - 20%.

Chapter 6 Conclusion

This research has presented two traditional models of vehicle routing problem, and has compared two traditional models' results with the in-house vehicle routing optimization software' result. The objective of this research was to find the best algorithm based on the total cost. The research results showed that in-house optimization software has the smallest cost with the same data. Also, this research analyzed the relevant factors and demonstrated why they play an important role in obtaining better results.

However, the traditional models are not completely defecting because the in-house optimization software algorithm is also based on several traditional models by making them work together. In this research we found why the traditional models got bad results in order to continue the future research on how to improve the in-house optimization software.

This research gives a method to improve the software algorithm. That is, it compares another algorithm in the same filed condition. In this research, we ran the same set of data to see the results from different algorithms in order to find the advantage and disadvantage for each algorithm, and then use each algorithm's advantage for our

software.

Chapter 7 Limitation

This research has some limitations. In terms of data collection, our sample is small. It just covers one state in the U.S, and in reality, companies always operate the fleet in a large region, which is usually more than one state. In reality, the capacity of truck in a fleet is different. Also, no item remains at a perfect inventory level to meet with customers' demand on one hundred percent of the time. That means, the demand of each store should be changed in a little range. Also, the route of the truck shipping should be changed too. If this case happens in a short time, this issue will be solved. In addition, as we analyze with the sensitivity method, obviously, the oil price is changed within an interval, but some other factors may be changed as well. For example, we mentioned that the demand of the stores may be changed, and so does the labor fee.

Another assumption made in our analysis is shipping time. Some research papers discuss the vehicle routing problem with the time window. This is the way that the company operates in real life situation. In our research, the two traditional algorithms do not take into account the shipping time and in the in-house optimization software, in order to make it more comparable with the traditional models. In this research, for the two

traditional models, we have assumed the shipping time to be 24 hours per day. Actually, not all of the stores are available for receiving the shipment during the night time.

For the linear programming algorithm, we took one of the Lincoln and one of the Omaha stores as the sub-supply center, and the main distribution center's duty was to support the good for these two sub-supply centers. And here, the linear programming algorithm was used in these two sub- supply centers because the AB: QM is not fit for the constraints up to 50. The result would be better if we considered the whole situation of the stores and supply centers.

Chapter 8 Future Research

Future direction of our research would be in two parts: one is focus on the new algorithms for the vehicle routing software. The different software's process the data differently depending on the model they use. Therefore, when the people use the mathematical modeling for the software, they need to think about how to make the model simple and powerful. The other one is how to cut price of the professional vehicle routing software. Recently, not every transportation company can buy this kind of expensive software. Thus, the software engineers and theorists should cooperate to design the high cost performance software in the future.

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Appendix A The Wal-Mart distribution center and stores in Nebraska 1:

store number	Store number	Street	City	State	Zip
1	3620	N 6th st	Beatrice	NE	68310
2	10504	S 15th st	Bellevue	NE	68123
3	510	Linden Street	Chadron	NE	69337
4	818	East 23rd St	Columbus	NE	68601
5	1800	East 29th Street	Crete	NE	68333
6	2831	Hwy 15	Fairbury	NE	68352
7	3010	E 23rd Ave N	Fremont	NE	68025
8	3501	S Locust St	Grand Island	NE	68801
9	2250	No Diers Ave	Grand Island	NE	68803
10	3803	Osborne Drive West	Hastings	NE	68901
11	5411	N Second Avenue	Kearney	NE	68847
12	200	Frontier Street	Lexington	NE	68850
13	4700	N 27th Street	Lincoln	NE	68521
14	8700	Andermatt Dr	Lincoln	NE	68526
15	1902	West B	Mccook	NE	69001

Appendix B The Wal-Mart distribution center and stores in Nebraska 2:

store number	Store number	Street	City	State	Zip
16	2101	S 11Th Street	Nebraska City	NE	68410
17	2400	Pasewalk Ave	Norfolk	NE	68701
18	1401	South Dewey St	North Platte	NE	69101
19	6304	North 99th Street	Omaha	NE	68122
20	18201	Wright St	Omaha	NE	68130
21	16960	W Maple Rd	Omaha	NE	68116
22	12850	L Street	Omaha	NE	68137
23	8525	S 72st St Plaza	Papillion	NE	68133
24	3322	Avenue I	Scotts Bluff	NE	69361
25	1326	280th Road	Seward	NE	68434
26	3001	Silverberg Drive	Sidney	NE	69162
27	1601	Cornhuskers Drive	South Sioux City	NE	68776
28	101	East David Drive	York	NE	68467

DC	3001	E State Farm Rd	North Platte	NE	69101

Appendix C Matlab code of saving heuristic

```
clear;
S=zeros(28,28);
K=zeros(275,3);
M=zeros(275,3);
ID=zeros(275,1);
IX=zeros(275,1);
L=xlsread('D:\data.xls','L','B2:AC2');
B=xlsread('D:\data.xls','B','B2:AC29');
D=xlsread('D:\data.xls','D','B2:AC2');
C=20;
E=0;
n=0;
for i=1:28
   for j=(i+1):28
     E=D(i)+D(j);
     if (E<=C)
        S(i,j)=L(i)+L(j)-B(i,j);
     else
        S(i,j)=0;
     end;
   end;
end;

for i=1:28
   for j=1:28
     if S(i,j)>0
     n=n+1;
     K(n,:)=[S(i,j) i j];
     end;
   end;
end;
[ID,IX]=sort(K(:,1),'descend');
for i=1:275
   M(i,:)=[ID(i) K(IX(i),2) K(IX(i),3)];
end;

for i=1:275
```

```
    a=M(i,2);
   b=M(i,3);
  for j=(i+1):275
     if
display(M);
```

Appendix D AB: QM interface.