# A decision support system for goods distribution planning in urban areas

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## School of Graduate Studies

This is to certify that the thesis prepared

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and submitted in partial fulfillment of the requirements for the degree of

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complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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# ABSTRACT

## A decision support system for goods distribution planning in urban areas

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Efficient goods distribution planning is vital to ensure high business revenues for logistics operators and minimize negative impacts on the environment. In this thesis, we address three main problems related to goods distribution planning in urban areas namely customer allocation, order scheduling, and vehicle routing. A three step approach is proposed. In the first step, we use Nearest Neighbour and Tabu Search for balanced allocation of customers to logistics depots. In the second step, Genetic Algorithm approach is used to perform order scheduling at each depot for the allocated customers. In the third and the last step, we perform vehicle allocations and generate fastest paths for goods delivery to customers using modified Dijkstra's algorithm. All these decisions are made considering realistic conditions associated with goods distribution in urban areas such as presence of congestion, municipal regulations, for example vehicle sizing, timing and access regulations etc. The objective is to minimize total distribution costs of logistics operators under these constraints.

A prototype decision support system is developed integrating the proposed approaches for goods distribution planning in urban areas. The strength of the proposed decision support system is its ability to generate fast and efficient solutions for balanced customer allocation, dynamic order scheduling, vehicle allocation considering environmental constraints and fastest path generation under dynamic traffic conditions. The proposed model results are verified and validated against other standard approaches available in literature.

# Dedication

I dedicate my work to my devoted wife Atena, whose generosity and support has been constant and unconditional throughout this process, and whose love and commitment to our little one, Artan, has been a constant source of encouragement. I also dedicate this work to my always loving family, my patient parents, my lovely son Artan and my brother-in-law Hamid, he has been the perfect role model for me.

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I would like to express my deep and sincere gratitude to my supervisor, Professor Anjali Awasthi. Her wide knowledge and her logical way of thinking have been of great value for me. Her understanding, encouragement and personal guidance have provided a good basis for the presented thesis.

She has always dedicated her time in research. Not only has she taught me and trained me how to be a good researcher, but she has also shown me how to utilize my time efficiently to get to my expected goal. Furthermore, she is a very understanding and patient professor. She has always put me in the right direction. Most importantly, I will forever consider her as my greatest advisor.

I owe my thanks to my always-loving wife Atena and my lovely son Artan. Without their encouragement and understanding it would have been impossible for me to finish this work. A special gratitude for their loving support is due to my parent, my parents-in-law, my sisters and my brother.

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## List of Acronyms

| | |
|---|---|
| GA | Genetic Algorithms |
| TS | Tabu Search |
| ACO | Ant Colony Optimization |
| SA | Simulated Annealing |
| LA | Location Allocation |
| DC | Distribution Centers |
| MCDA | Multi-Criteria Decision Analysis |
| TOPSIS | Technique for Order Preference by Similarity to an Ideal Solution |
| SAW | Simple Additive Weighting Model |
| GDS | Goods Distribution Software |
| NN | Nearest Neighborhood |
| API | Application Program Interface |
| BSC | Balanced Score Approach |
| DP | Dynamic Programming |
| GSC | Green Supply Chain |
| GUIs | Graphical User Interface |
| LCA | Life Cycle Analysis |
| QA | Quality Assurance |
| SC | Supply Chain |
| SCM | Supply Chain Management |
| SCN | Supply Chain Network |
| SWOT | Strengths, Weaknesses, Opportunities, Threats |
| GRA | Greedy algorithm |

# Chapter 1:

# Introduction

## 1.1 Background

Goods distribution in urban areas is an important activity. All distribution systems need to maintain and protect our lifestyles, as well as serve industries and business trade activities for wealth generation. Goods distribution should support the city economy in two ways: by generating income and by creating employment. However, goods transport is also responsible for traffic and negative environmental impacts on cities such as congestion, pollution, noise, etc.

The distribution of goods in the city center has been the subject of many academic writings and discussions. It is critical for companies to provide goods to their customers at the desired times. Any kind of slack in the distribution may be the cause of lost profit and lost customers. Some critical issues related to goods distribution that need to be addressed for high quality service are: how many vehicles to use for delivery, which terminals to use, how the goods should be consolidated, how to generate vehicle routes, how to schedule vehicle trips etc. Considering the traffic conditions on one hand and the economies on the other hand, plays a dilemma for logistics operators on this issue. The importance of on-time distribution and the cost optimization are equally important objectives for logistics operators and should be carefully planned for efficient goods distribution planning.

The traffic conditions of the city, the client locations, location of the distribution centers, and the types of vehicle available with the logistics operator play a vital role in planning of efficient distribution of goods in the city. Therefore, when designing distribution systems, the companies should consider these factors to mitigate resulting air pollution, noise, congestion, and other environmental impacts.

There are three different types of distribution systems related to the business strategy of the company. The first category of distribution system is the "selective distribution". In this system, the company would target their products to specific outlets where their products would best fit. The second type of distribution system is the "intensive distribution". In an intensive distribution, the company would try to sell their products to as many different outlets as possible. Lastly, there's the "exclusive distribution" system. In this one, the company would look for a very limited number of outlets that would most likely specialize in specific goods.

The objectives of companies' logistics, and the idea of achieving an efficient distribution system of goods to the clients cannot be sustained without involving the interests of various stakeholders. Basically, there are four stakeholders involved in urban goods transport: the shippers (vehicles), the city administrators, the clients and the carriers or transport operators. The goal of city administrators is to improve economy and reduce environmental impacts whereas the goal of clients or city residents is to have improved quality of life. The shippers and transport operators, on the other hand, want to distribute goods in minimum time. Thus, to come up with an efficient distribution system, the objectives of each of these stakeholders must be respected to achieve overall system goals.

## 1.2 Research Objectives

This thesis presents a methodological framework and a prototype decision support system (DSS) for goods distribution planning in urban areas. Three main problems are investigated. The first problem is related to customer allocation, that is, how to perform balanced allocation of clients to different depots considering their capacity constraints and presence of urban freight regulations in the delivery area. Secondly, how to perform scheduling of received orders from customers considering their requested times and delivery constraints on city road networks. Thirdly, we investigate which vehicles to allocate to deliver scheduled orders in time and which vehicles routes to use for distribution. It can be seen that these three objectives are inter-related to each other in efficient goods distribution planning.

## 1.3 Research Structure

The critical purpose of this thesis is to design and develop better and efficient approaches for goods distribution from logistics depots to customers in urban areas considering dynamic traffic conditions and city freight distribution constraints imposed by municipal administrations. To achieve this objective, we followed a structured approach to conduct the proposed research. Figure 1.2 presents the various steps involved in conducting research for this thesis. The first step is defining and establishing research goals followed by literature review, identification of methods and techniques for resolving the problems involved, implementing the core research by using heuristic based methods, model testing and validation, and delivering the results of the study.

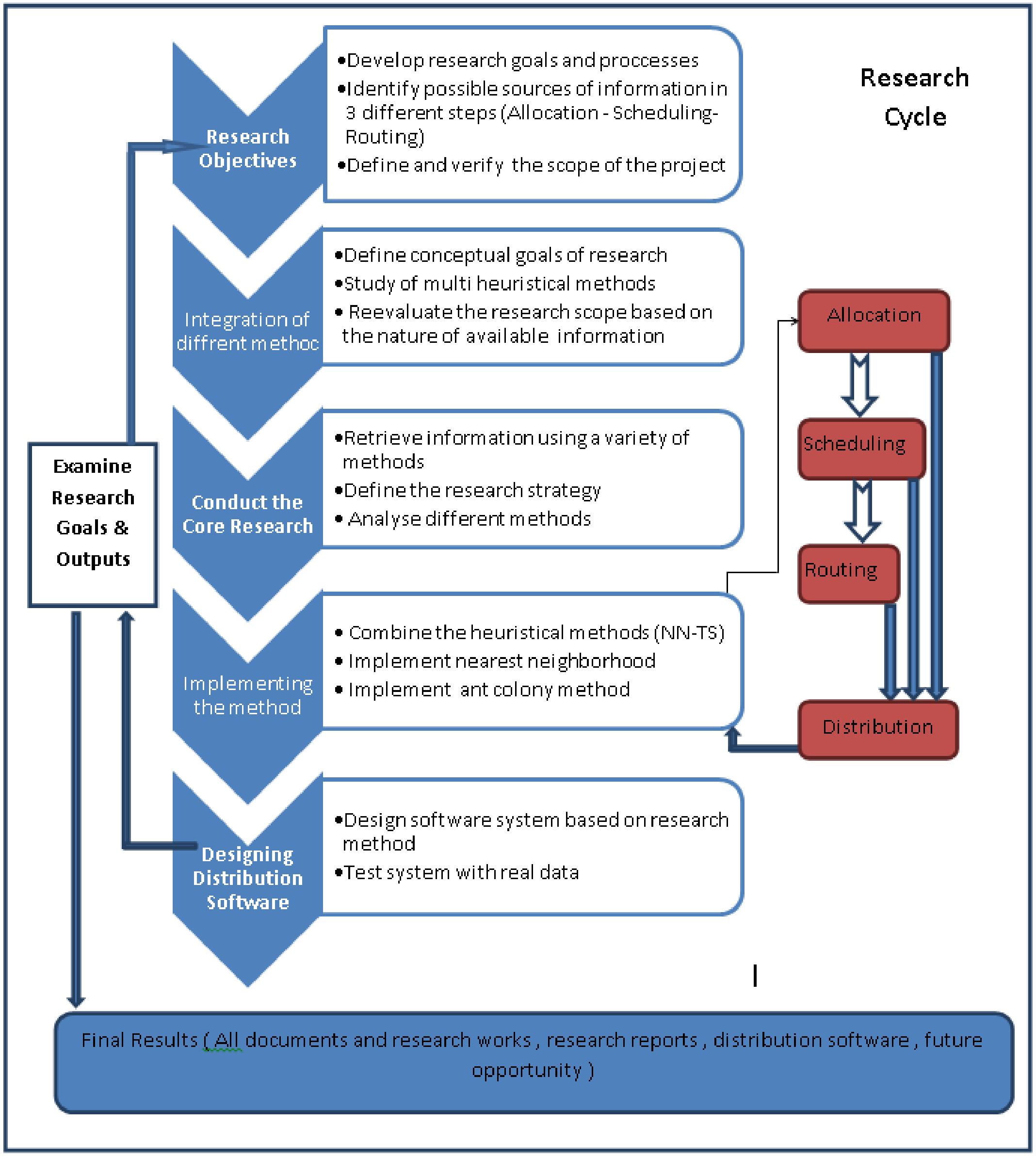



**Figure 1.1: Research Planning Steps**

## 1.4 Thesis Outline

Chapter 1 of this thesis contains the Introduction on goods distribution planning in urban areas.

In Chapter 2, we present the problem statement.

Chapter 3 presents the literature review on city logistics under three categories namely customer allocation, order scheduling and vehicle routing.

Chapter 4 presents the proposed solutions approaches for the customer allocation, order scheduling and vehicle routing problems.

Chapter 5 presents numerical application of the proposed solution approaches for the customer allocation, trip scheduling and vehicle routing problem.

Chapter 6 presents the prototype decision support system based on the proposed solution approaches in the thesis.

Finally, the conclusions and future works are presented in Chapter 7.

# Chapter 2:

# Problem Statement

The main problem investigated in this thesis consists of goods distribution planning in urban areas under dynamic traffic conditions and urban freight regulations imposed by municipal administration. This problem can be categorized into three sub-problems as follows.

- Balanced Allocation of customers to logistics depots,
- Dynamic Scheduling of customer orders at each depot,
- Vehicle allocation and route planning under dynamic traffic conditions.

The customer allocation problem involves balanced allocation of customers to logistics depots considering capacity constraints of logistics depots, freight movement constraints imposed by city traffic administrators and congestion situation of the city. The objective is to minimize total distribution costs.

The second problem involves scheduling of customer orders considering the capacity constraints of vehicles, and city delivery constraints such as time and access regulations. The objective is to minimize service time and total distribution costs.

The third problem involves vehicle allocation to scheduled customer orders and planning of fastest routes for delivery of goods to customer considering dynamic traffic conditions, city congestion, and time and access regulations imposed by municipal administrations on freight movement inside city centers. The objective is to minimize vehicle allocation costs and travel times on road networks.

# Chapter 3:

# Literature Review

In this chapter, we present existing literature on goods distribution planning namely in the areas city logistics, customer allocation, order scheduling, and vehicle routing. The data used for literature review was collected from hardcopy readings like published books, references, magazines, etc. and online searches. The online sources used were www.sciencedirect.com, www.gdrc.org, www.greenlogistics.org, www.dl.acm.org; www.ebsco.com; www.metapress.com; www.jstor.org; www.scopus.com; and www.mansci.journal.informs.org.

## 3.1 City Logistics

Taniguchi *et al.* (1999) defines City logistics as the process for totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy. The aim of city logistics or urban goods distribution is to optimize the delivery of goods or services in city areas, by considering the improvement of the efficiency of city transportation, reducing traffic congestion and decreasing environmental impacts (Taniguchi, 2000).

Distribution planning of goods in urban areas can be done in several ways. Due to high scale of traffic, the strongly dense cities can be serviced through an efficient customer allocation system. The goal is to evenly divide the clientele between different depots and from each of these depots, smaller vehicles can be used to service the customers in the city for delivery or pick up of goods and services. The use of smaller vehicles in the city is more convenient since they will cause little congestion problems and conform to vehicle sizing restrictions of the cities; however the issue of cost must also be considered (Crainic et al., 2007).

In recent years, we observe a growing trend in the number of studies carried out in the field of city logistics. Quak and De Koster (2009) study goods distribution in urban areas considering urban policy restrictions and environment. Anderson et al. (2005) study the role of urban logistics in meeting policy makers' sustainability objectives. Browne and Allen (1999) investigate the impact of sustainability policies on urban freight transport and logistics systems. Crainic et al. (2007) propose models for evaluating and planning city logistics transportation systems. Dablanc (2007) investigates the problem of goods transport in large European cities. Muñuzuri et al. (2005) propose city logistics solutions applicable by local administrations for urban logistics improvement. Visser et al. (1999) study urban freight transport policy and planning. Polimeni and Vitetta (2010) propose demand and routing models for urban goods movement simulation. Ogden (1992) studied policy and planning aspects of urban goods movement. Eriksson and Svensson (2008) investigate efficiency in goods distribution collaboration in cities. Brugge (1991) study logistical developments in urban distribution and their impact on energy use and the environment.

In the next sections, we will address the existing literature on city logistics under three main areas namely customer allocation to logistics depots, order scheduling of customers at depots, and route planning for delivery vehicles from depots.

## 3.2 Customer Allocation to Logistics depots

Allocation of customers to different depots is defined as the act of assigning each of the customers to different depots through replacing, or repositioning to ensure balanced allocation or uniform load distribution on all logistics depots. According to Hallam (1913), Customer allocation can be regarded as an instrument to solve conflicting traffic demand problem for companies by making a balance. Figure 3.1 shows an illustration of customer allocations at different echelons of a supply chain network.

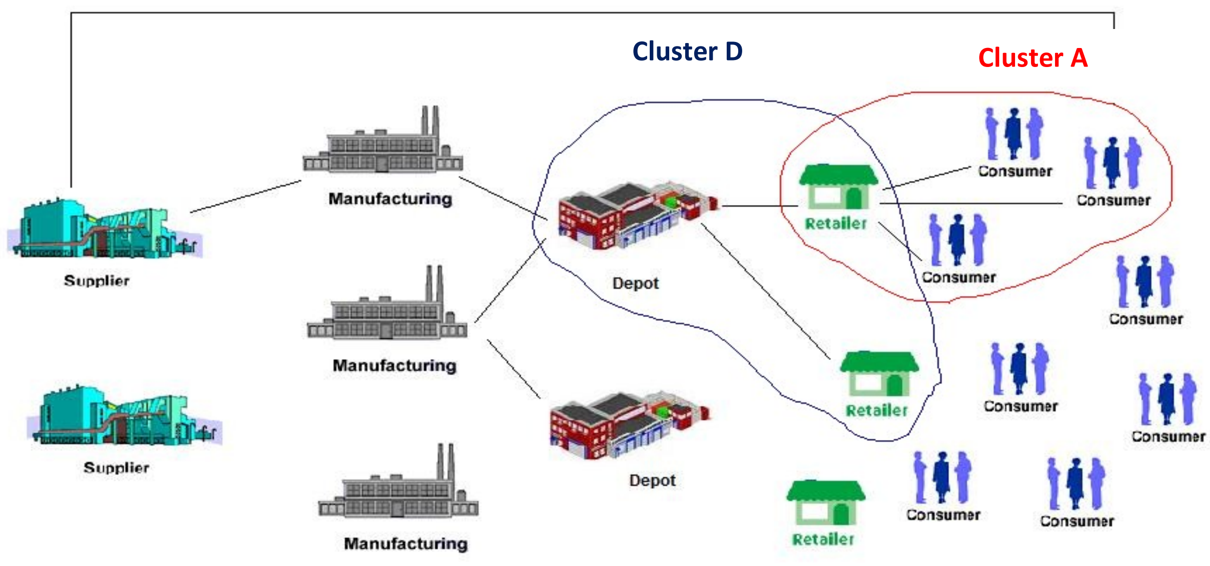



**Figure 3.1: Customer Allocation schema under supply chain network**

Determining the allocation mechanism for clients and deciding location of depots are complex tasks. They depend on the companies' customer service level, competitive advantage in distribution and inventory cost structures. In fact, company costs are influenced by the clients' allocation to facilities, places and sizes of depots. The optimum number of company's depots and client's allocation depends on a number of factors such as the nature of the product, the size and geographical deployment of the company market, the current and potential sales in the territory, the extent of seasonality of demand (if applicable), the level of peak demand, the number of distributors/retail outlets, the acceptable order-execution time, the possible speed of shipment of stocks, the cost involved in operating warehouses etc.

Allocation of clients is generally done on the basis of minimum distance between the delivery center and client. However, many other criteria can also be used such as allocation of customers by type, such as residential, business, trader, government, staff, etc; allocation of customers to subsets such as doctors, lawyers, teachers, etc; allocation of customers to categories, such as VIP, professional, private, major, etc; allocation of customers to groups such as major account, large business, small business, residential, government, etc. Future business requirements may also influence the decision of allocation.

Choosing the exact locations of depots is as important as choosing their number and capacity (Aikens, 1985). The locations must be suitable in terms of market factors, availability of transport facility, rent rates, commercial suitability of the location, implications of local lives, etc. The decision on the sizes of the depots is directly related to the total number of depots and their sales potential in each territory. Depot location and customer allocation costs are related to each other. The small sized allocations are uneconomical compared to the larger ones. At the same time, if the sales projected are small, allocation has to be small.

In literature, very few approaches have addressed the customer allocation problem. Zhou et al (2002) perform balanced allocation of customers to multiple distribution centers in a supply chain network using Genetic Algorithm approach. Chan and Kumar (2009) use multiple ant colony optimization approach for allocation of customers to distribution centers. Rajesh et al. (2011) using simulated annealing for balanced allocation problem. Ren (2011) presents different metaheuristic approaches to address the balanced customer allocation problem. Fazel-Zarandi (2009) address a location-allocation problem that requires deciding the location of a set of facilities and allocation of customers to those facilities under facility capacity constraints, and the allocation of the customers to trucks at those facilities under truck travel distance constraints. Huang and Liu (2004) propose bilevel programming approach to optimizing a logistic distribution network with balancing requirements. Min et al. (2005) propose a genetic algorithm approach for balanced allocation of customers to multiple warehouses with varying capacities. Kleywegt et al. (2002) perform customer allocation considering forecasting demands, transportation conditions, and general routing conditions in recent years. Dondo and Cerda (2007) present a cluster based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows. Nikolakopoulou et al. (2004) developed a heuristic algorithm to balance the vehicle time utilization by partitioning a distribution network into subnetworks. Chen and Jiang (2004) propose a reseau-dividing algorithm for distributing products of Hangzhou Tobacco Company. Meyer (2011) analyze the problems of vehicle routing and break scheduling using a distributed decision making perspective.

Few papers consider customer allocation to depots for goods distribution planning under dynamic traffic conditions. Since, our customer allocation problem addresses urban areas, it is vital to take into account the presence of any time regulations, access regulations, congestion pricing schemes etc imposed by the municipal administration in the customer delivery zones. Failure to do so will significantly impact the distribution costs.

## 3.3 Scheduling of customer orders

Scheduling is the process of defining a precise timing plan for performing the activities involved. The objective is to maximize operational efficiency and minimize costs by appropriate allocation of resources to right tasks, at right times, on right equipment. Scheduling can be done in following ways:

- As soon as possible
- By a specified date
- Within a specified number of working days.
- By priority list which can contain priority orders, priority equipments, priority delivery times, priority regions.

The need for scheduling arises from the requirement of most modern systems to perform multitasking or execute more than one process at a time. Figure 3.2 presents a precedence diagram showing the ordering of different tasks 1-7 which must be respected during the scheduling process.

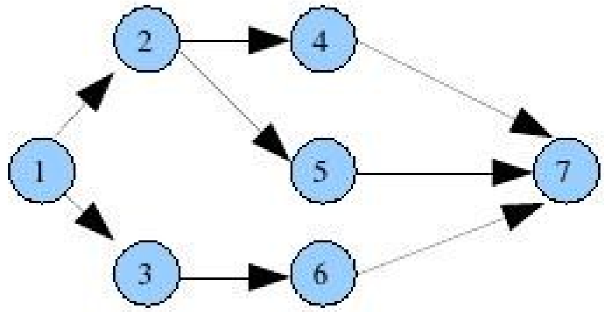



**Figure 3.2: Precedence in scheduling**

In goods distribution, productivity is completely linked to how well companies optimize their resources (vehicles, facilities, drivers, pallets etc.) and reduce waste (travel time, delays, excess inventory) while increasing efficiency to achieve high levels of service quality towards customers.

Finding the best way to maximize efficiency in a goods distribution process can be extremely complex. Even on simple projects, there are multiple inputs, multiple steps, many constraints and limited resources. In general, a scheduling problem consists of:

- A set of jobs that must be executed;
- A finite set of resources that can be used to complete each job;
- A set of constraints that must be satisfied
    - Temporal Constraints–the time window to complete the task
    - Procedural Constraints–the order each delivery must be completed
    - Resource Constraints - is the resource available
- A set of objectives to evaluate the scheduling performance.

Scheduling problems are complex problems, and known in computer science as an NP-Hard problem. This means that there are no known algorithms for finding an optimal solution in polynomial time. Therefore, heuristic algorithms and metaheuristics are often used to address these problems.

Yang (2005) study the complexity of customer order scheduling problems on parallel machines. Park et al. (2003) present a hybrid genetic algorithm for the job scheduling problem. Darrell (1991) proposes a genetic operator that generates high-quality solutions for sequencing and ordering problems for production line at HP manufacturing site in Fort Collins, Colorado. Hall (2001) consider a variety of scheduling problems regarding which job should be dispatched to a customer at the earliest fixed delivery date. Lei and Guoqing (2010) find a precise schedule of order processing at the supplier and order delivery from the supplier to the customers that minimize the total distribution cost with deadline constraints. Jaumard et al. (1998) introduced a generalized linear model for the complex nurse scheduling problem considering workload, rotations and day-off, etc.

Vehicle scheduling problem has been widely studied in literature. Clarke and Wright (1964) perform scheduling of vehicles from a central depot to a number of delivery points. Chen (2010) studied order scheduling with delivery vehicles routing in an integrated way for two-echelon supply chain system. Campbell and Savelsbergh (2005) propose efficient insertion heuristics for vehicle routing and scheduling problems. Eglese et al. (2005) study the grocery superstore vehicle scheduling problem. Baita et al. (1998) present different solution approaches for the vehicle scheduling problem in a practical case of Trieste, Italy. Li et al. (2008) present a heuristic approach, incorporating an auction algorithm and a dynamic penalty method for truck scheduling for solid waste collection in the City of Porto Alegre in Brazil. Tsuji and Koizumi (2007) propose a practical method for solving the delivery scheduling problem using a distributed approach. Solomon (1997) proposes algorithms for vehicle routing and scheduling problems under time window constraints.

Vehicle scheduling under dynamic context has been investigated by Yang et al. (1999) who propose online algorithms for truck fleet assignment and scheduling under real-time information. Potvin et al. (2006) study vehicle routing and scheduling with dynamic travel times. Chien (1993) determine profit-maximizing production/shipping policies in a one-to-one direct shipping, stochastic demand environment. Ichoua et al. (2003) study vehicle dispatching with time-dependent travel times. Fu (2002) propose heuristics for scheduling of dial-a-ride paratransit under time-varying stochastic congestion. Maden et al. (2009) study vehicle routing and scheduling with time-varying data.

## 3.4 Vehicle allocation and routing planning for goods delivery

Vehicle allocation is the process of allocating vehicles to deliver scheduled orders. The vehicle selection is performed taking into consideration vehicle capacities, emission levels, noise, and any sizing restrictions imposed by the city on goods delivery in specific areas.

The route generation process involves computation of least travel time path between a given origin-destination pair considering travel distance, road congestion, traffic incidents, and any access regulations imposed by municipal administration in the delivery areas.

Design and planning vehicle routing and its extensions are very sophisticated problems in transport operations. They have significant importance in the operations research area and have been investigated by several researchers over years. The vehicle routing problem (VRP) was initially formulated as an integer program by Dantzig and Ramser (1959). In early 1960s, small size instances of the problem (30-100 customers) were solved using route-building, route-improvement and two-phase heuristics (Clarle et al., 1969, Gaskell, 1967). In the 1970s, a number of two-phase heuristics were proposed for large problem size instances (Nelson, 1972, Gillett and Miller, 1974, Christofides et al., 1979). In 1980s, mathematical programming based approaches were put forth by Fisher and Jaikumar (1981) for vehicle routing problem with 50 customers. Baker (1983) presents an exact algorithm for the time-constrained traveling salesman problem. Dror and Trudeau (1989) propose a savings approach based on split delivery routing.

As the size of the problems became large, it was found that mathematical programming based approaches were not enough to address the problem (Braysy and Gendreau, 2005) and therefore, heuristics and metaheuristics were proposed in the 1990s by Basnet et al. (1999), Bramel and Simchi-levi (1995), Savelsbergh and Sol (1997), Laporte (1992) , and Taillard et al. (1997). Ho and Haugland (2002) propose a tabu search heuristic for the vehicle routing problem with time windows and split deliveries. Montemanni et al. (2005) solves vehicle routing problem using ant colony optimization. Toth and Vigo (2003) devised a granular tabu search method for the vehicle routing problem. Reimann et al. (2004) propose D-ants: a Savings based ants divide and conquer algorithm for the vehicle routing problem. Arbelaitz and Rodriguez (2000) propose Simulated Annealing for the Vehicle Routing Problem. Liu and Chang (2006) propose multi-objective heuristics for the vehicle routing problem. Lu et al. (2006) solve optimal vehicle routing problem based on fuzzy clustering analysis. Some authors propose hybrid approaches based on metaheuristics for vehicle routing problem. Berger and Mohamed (2003) propose a hybrid genetic algorithm for the capacitated vehicle routing problem. Li et al. (2011) propose a hybrid approach of GA and ACO for VRP.

Vehicle routing for stochastic customer demands has been investigated by Teng et al. (2003), who apply three metaheuristics based on simulated annealing, tabu search and threshold accepting for vehicle routing under stochastic demand. Bianchi et al. (2004) present metaheuristics for the vehicle routing problem with stochastic demands.

The shortest paths are often used in route planning. However, under dynamic traffic conditions, fastest paths instead of shortest paths should be used to accommodate the congestion delay, or delays arising from presence of other incidents such as accidents, time regulations. Fu and Rilett (1998) study shortest path problems in traffic networks with dynamic and stochastic link travel times. Zhan et al. (1998) presents shortest path algorithms and their application on real road networks.

Vehicle routing under dynamic travel times has become a popular area of research in recent years, especially with the importance of growing congestion in cities. Fleischmann et al. (2004) study time-varying travel Times in vehicle routing. Kim et al. (2005) perform optimal vehicle routing with real-time information. Cheung et al. (2008) study dynamic routing model and solution methods for fleet management with mobile technologies. Powell (1990) studied real-time optimization for truckload motor carriers. Faccio et al. (2011) propose a waste collection multi objective model with real time traceability data.

For a review on classical and modern local search neighborhoods for the vehicle routing problem, please refer to Funke et al. (2005). A good review on metaheuristics for the vehicle routing problem with time windows can be found in Braysy and Gendreau (2005), and Sun et al. (2006).

### 3.5 Decision support systems for goods distribution planning

A decision support system is an automated software (or tool or utility) to assist the decision maker in fast and efficient problem solving by allowing data storage, visualization options, solution generation, scenario analysis, etc.

In literature, we find some papers on vehicle routing and scheduling decision support systems for large size instances of the problem. Ruiz et al (2004) present a decision support system for a real vehicle routing problem based on enumerative algorithm and Integer programming. Dutta et al (2007) present an optimization based decision support system for strategic planning in a Pharmaceutical industry. Zografos et al (2008) present a decision support system for integrated hazardous material routing and emergency response decisions based on integer programming. Gayialis and Tatsiopoulos (2004) design an IT-driven decision support system for vehicle routing and scheduling using Geographic Information System (GIS) and Enterprise Resource Planning (ERP) software. Badran and El-Haggar (2006) present an optimization based DSS for municipal solid waste management in Port Said–Egypt. Osvald and Stirn (2008) propose a vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. Nuortio et al. (2006) propose a variable neighborhood thresholding metaheuristic for solving real-life waste collection problems.

Shahzad and Tenti (2009) study efficient distribution systems for goods delivery in the city centres. Zeimpekis et al. (2007) propose a dynamic real-time vehicle management system for urban distribution. Taniguchi and Shimamoto (2004) study intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. Ghandforoush and Sen (2010) propose a DSS to manage platelet production supply chain for regional blood centers. Hu and Huang (2007) propose an intelligent solution system for a vehicle routing problem in urban distribution.

The key requirements that a vehicle routing and scheduling decision support system should fulfill besides generating efficient solutions are fast response time, user friendly interface, easy integration ability with other software, ability to treat and store large volumes of data, well documented, and be easily customized with respect to changing customer needs. Slater (2002) provides specification for a dynamic vehicle routing and scheduling system.

# Chapter 4:

# Solution Approach / Methodology

Our solution approach for goods distribution planning in urban areas addresses the following three problems:

- Balanced Customer Allocation,
- Dynamic Order Scheduling,
- Vehicle Allocation and Route planning under dynamic traffic condition.

The first problem investigated for goods distribution planning is allocation of clients or customers to different depots. A balanced allocation of customers to the DCs can be helpful in a better management of the customer demand, which can further result in better customer service. In the city context, the geographical location of customers, presence of access regulations, distance to logistics facility, order types, product types are some of the important criteria to be considered during the allocation process. We propose a hybrid approach based on Nearest Neighbor Algorithm and Tabu Search to address this problem.

The second step is order scheduling. One of the important things for addressing the scheduling problem is a priority list. This list consists of customer orders prioritized based on the preferred time windows, priority clients, and presence of access and timing regulations in the delivery regions. We apply Genetic Algorithms for order scheduling of customers obtained from step 1.

The third step involves vehicle selection and routing for fulfilling customer demands. The vehicle selection for scheduled orders depends on the vehicle capacities, their emission and noise levels, and the sizing regulations imposed on vehicles by municipal administration in the delivery area. We use a weighted scoring method for vehicle selection for serving scheduled orders. The route planning involves generating fastest path for goods delivery to vehicles which can depend on a number of factors such as travel distance, congestion, presence of traffic incidents, and any access-timing regulations on delivery vehicles inside the city centers. We propose modified Dijkstra's algorithm for generating fastest paths for delivery vehicles. Figure 4.1 presents the three steps involved in the solution approach.

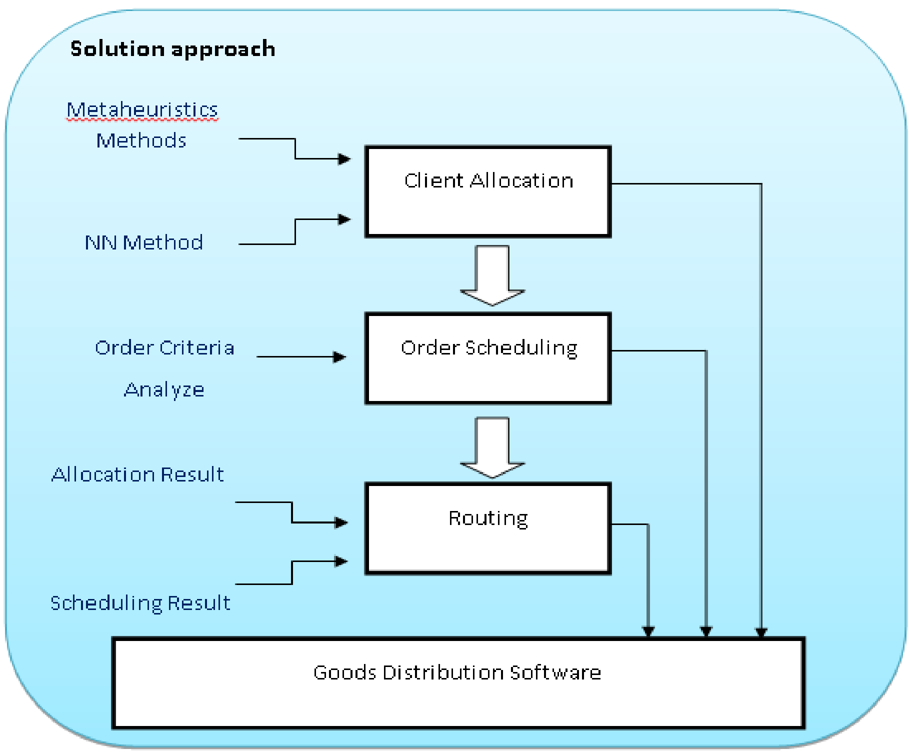



**Figure 4.1: Proposed solution approach**

## 4.1 Customer Allocation

We propose a hybrid approach based on Nearest Neighbour (NN) and Tabu Search (TS) for performing balanced customer allocation to logistics depots. Besides, we also tested a number of other heuristics to compare the performance of our approach.

To perform the customer allocation, we will use weighted travel time in order to take into account the presence of city traffic conditions and access-timing regulations imposed by municipal administration in urban areas. The weighted travel time = *w*1*Basic Travel Time + *w*2*Access regulation delay+ *w*3*Time regulation delay+*w*4*Congestion delay where *w*1, *w*2, *w*3 and *w*4 represent the weights of criteria Distance, Access Regulation delay, Time regulation delay, and congestion delay respectively.

The details of the proposed approach and other approaches used for its performance comparison are presented as follows:

### 4.1.1 Nearest Neighbor

In the Nearest Neighbor approach, we pick each depot one by one and allocate the nearest customers to it maintaining the load balancing constraints. The distance between any two given points ($x_1$, $y_1$) and ($x_2$, $y_2$) is calculated using the following formula:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

The maximum allowed number of clients (or load) for each depot is given by

$$w = \frac{m}{n}$$

Where $m$ is the total number of clients and $n$ is the total number of depots.

#### 4.1.2 Tabu Search

Tabu search is a meta-heuristic technique used to solve optimization problems by tracking and guiding the search (Golver and Laguna, 1997). Tabu search begins by setting up a set of feasible solutions then choosing certain solutions in the feasible neighbourhood subject to constraints of tabu list for searching the objective solution, and finally generating the solution. Tabu search enhances the performance of a local search method by using memory structures, once a potential solution has been determined then it is marked as tabu so that the algorithm does not visit that possibility repeatedly. TS focus on the problem of how to cut off large computation in the solution space so as to avoid long computation times and make the search quicker. The tabu list length is an important factor in TS for the reason that its length will affect the computation speed or the efficiency of the searching process and therefore be decided by the condition of problem or other factors that affect the TS process. Glover (1989)

**Method Description**

**Generate Initial Solution**

This step involves generating initial solution which include of opening all facilities, random allocation of clients, and evaluation of objective function for that solution.

**Initialize memory structures**

This step involves initialization of all memory structures used during the run of the tabu search algorithm. The memory structures involved are tabu list, short-term and long-term memories. The difference between short term and long term memory is that the short-term memory is the list of solutions recently considered. If a potential solution appears on this list, it cannot be revisited until it reaches an expiration point whereas the long-term memory is the rules that promote diversity in the search process (Glover and Laguna, 1997).

**Generate admissible solutions**

Generate a set of candidate moves from the current solution which is the result of finding nearest neighbourhood for each depots. A move describes the process of generating a feasible solution to the problem. For example, Add, Drop, Swap etc. In our case, all these three kind of moves are involved in allocating customers to logistics facilities or depots to generate a solutions considering to satisfy balance allocation

**Select best solution**

This step returns the best solution from the list of candidate solution. If the best of these solutions is not tabu or if the best is tabu but satisfies the aspiration criteria, the pick that move and consider it to be the new current solution, else pick the best move that is not tabu and consider it to be the new current solution. Repeat the procedure for a certain number of iterations. On termination, the best solution obtained so far is the solution obtained by the algorithm.

The tabu status of solution approaches is maintained for number of iterations, the number of previous solution being called the tabu tenure or tabu list length. Unfortunately, this may forbid moves towards attractive, unvisited solutions. To avoid such an undesirable situation, an aspiration criteria is used to override the tabu status of certain moves, it means if a certain move is forbidden by tabu restriction, then the aspiration criteria, when satisfied, can make this move allowable.

**Update memory structures**

To increase the efficiency of TS, long-term memory strategies can be used to intensify or diversify the search. Intensification strategies are intended to explore more carefully promising regions of the search space either by recovering elite solutions (i.e., the best solutions obtained so far) or attributes of these solutions. Diversification refers to the exploration of new search space regions through the introduction of new attribute combinations (Glover and Laguna 1997, Dorigo and Stutzle, 2004).

**Parameter setting**

Following parameters need to be set before running the TS:

- The number of random solutions to be generated from the current one.
- The tabu list size.
- Maximum number of non-improving iterations before termination.

**Neighbourhood**: A neighbourhood for this problem is defined as any other solution that is obtained by an exchange of any two clients in the solution where a balance allocation is considered. This always guarantees that any neighbourhood to a feasible solution is always a feasible solution. If we considering the distance between each client and depot at each iteration the neighbourhood with the best objective value (minimum distance) is selected.

The advantage of Tabu search is that it searches for good quality solutions over all the solution space. It examines the trajectory or sequence of solutions and picks the best in the neighbourhood iteration-wise, thereby, saving a lot of time in the process of computation (Joubert, 2007). However, the disadvantage of Tabu Search is that it repeatedly searches for solutions in its list, and therefore wastes a lot of time. Unfortunately, cutting off the runs due to a time-limit will result in non-feasible solutions.

### 4.1.3 Greedy Heuristic

In the Greedy Heuristic, we pick any one depot at random and perform customer allocation using the nearest distance criteria. The allocation continues till the depot reaches its maximum load. Then, another depot is picked at random and the same process is repeated. We continue this procedure until all the depots are reached or no more customers are available for allocation. The principal advantage of greedy algorithm is that it is cheap, both in space and time. Because the found solution may be local rather than global, the solution sometimes is not the desired one and we will have to search for it again with different measures.

Figure 4.2 presents an illustration of results obtained from the implementation of the Greedy algorithm for 3 depots and 15 customers. It can be seen that we do not obtain balanced allocation with Greedy heuristic and therefore, alternate solution approaches are required.

### 4.1.4 Traditional Allocation

The traditional allocation is the process commonly used in practice by the logistics operators. It involves allocating customers to logistics depots based on shortest distance. Sometimes, logistics operators may also perform allocations based on the convenience of delivery and/or availability of vehicles for delivery in those locations. In certain cases, logistics operators outsource services for their far located clients, and therefore, in those cases, the clients will be served by third parties and customer allocations be performed differently.

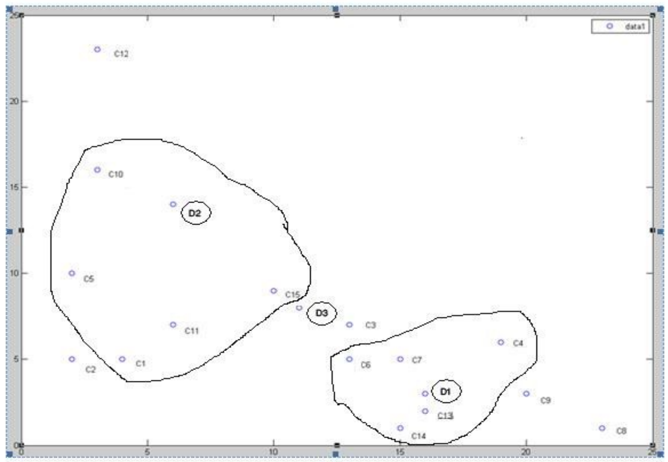



**Figure 4.2: Greedy algorithm allocation result**

### 4.1.5 Ant Colony Optimization

Ant Colony Optimization is a meta-heuristic technique based on the way ants search their foods, that is, finding the shortest route by cooperation. It is a probabilistic technique for solving complex computational problems by finding good paths through neighbourhoods. The various steps of Ant Colony Optimization are as follows:

- Initialization of ACO parameters and pheromone trials
- Solution (Tour) Construction
- Update of pheromone trials

The last two steps are carried out iteratively until no more improvement in objective function value for customer allocations can be observed.

### 4.1.6 Combination of Nearest neighbor and Tabu search algorithm

This approach takes into account the advantages of Nearest neighbor and Tabu search algorithms to generate good quality solutions. For the customer allocation problem, the Tabu search starts off with a valid random allocation, and then moves the clients to nearest logistics depots considering their capacity constraints. The algorithm terminates when no more improvement in solution quality is observed or the maximum computation time has been reached. The initial solution used in Tabu Search is generated using Nearest neighbor approach. Figure 4.3 presents the result of this hybrid approach.

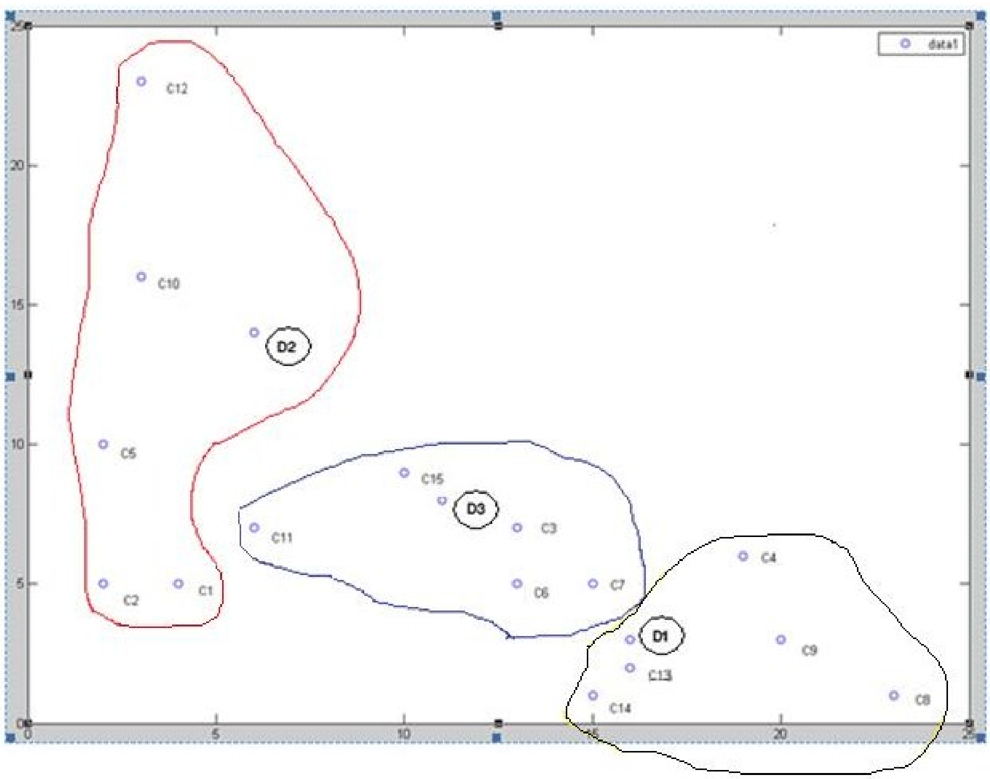



**Figure 4.3: Our study allocation result**

**NN and Tabu Search Pseudo-Code**

**NN**

```
Begin
    For all clients
        Find nearest neighborhood depots
End loop
```

**TS**

```
Begin
    Initialize the tabu list
    Initialize short-term
    Setup initial solution using NN
    Calculate the objective function for each depot
    Generate Neighborhood
    While (number if iterations <= Maximum value) or (improvement in objective function
        value <= 10^-3) do
        Begin
            Move
            Update Tabu list
            Update Short-Term Memory
            Check Aspiration Criteria
            Pick the best move s" that is non-tabu or aspiration criteria
            Setup new Neighborhood
        End
End
```

To compare the performance of our model results, we compared it with other heuristics mentioned above. Figure 4.4 presents the results of the different approaches. It can be seen that our proposed approach integrating Tabu search and nearest neighbourhood algorithms gives the best results in terms of uniform allocation of clients to the three depots and least distribution costs to customers.

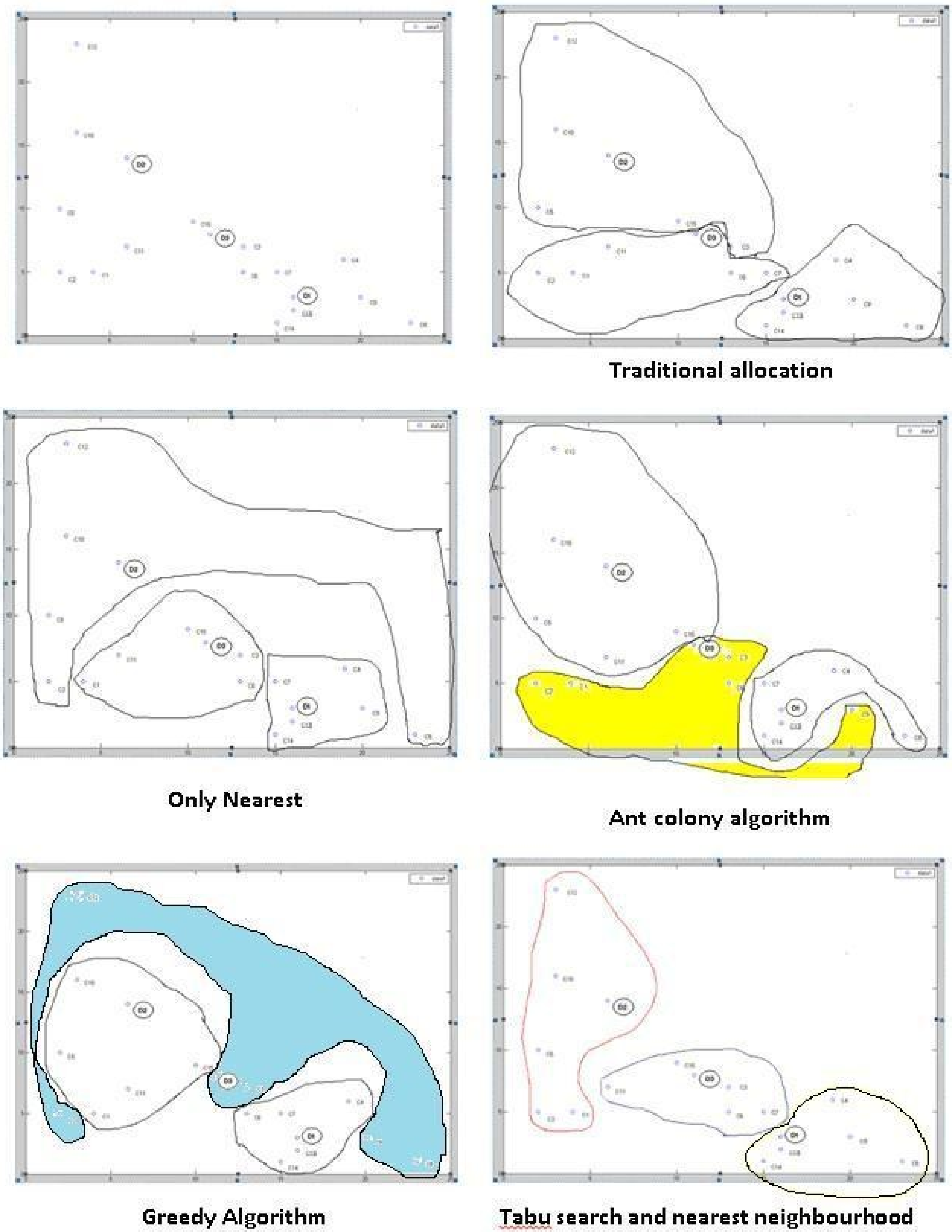



**Figure 4.4: Result of different customer allocation**

## 4.2 Order Scheduling

Order Scheduling involves generating a sequence or priority list for delivery of goods to customers. The goal is to achieve high quality service with least distribution costs. To perform order scheduling of customers residing in urban areas, the specificities of the city such as congestion, incidents etc. cannot be neglected. Besides, the packing time, loading time, unloading time, access times to city etc. are also important parameters that affect the order scheduling process. Therefore, considering the importance of these critical factors for performing order scheduling for urban areas, we propose a weighted scoring model for generating customer priorities. The weighted service time for each customer = $w1$*Loading Time + $w2$*Transit time+ $w3$*Historical Delay Time(of city) + $w4$*Packing Time + $w5$*Access Time to Facility where $w1$, $w2$, $w3$, $w4$ and $w5$ are the weights of criteria Loading Time, Transit time, Historical Delay Time(of city), Packing Time and Access Time to Facility. Each of these times (or criteria) has different weight which depends on the priorities of the logistics operator.

### 4.2.1 Genetic Algorithm

In order to solve to our scheduling plan by Genetic Algorithm, two main requirements are to be satisfied: First a string can represent a solution of the solution space, and second an objective function and hence a fitness function which measures the goodness of a solution can be defined.

We generate an initial population by using output of allocation section and each individual in the population is called a chromosome, then take this initial population and cross it, combining genomes along with a small amount of randomness (mutation).

We take this initial population and cross it, combining genomes along with a small amount of randomness (mutation).

**Fitness function**

Since, scheduling for this problem is a minimization in terms of minimizing the total travel time for delivering the orders, we consider below fitness function, where f(x) calculates total travel time or weighted client score value as an objective function of the schedule.

$$F(x) = \frac{1}{f(x)}$$

**Parents Selection Procedure**

To select the parents for crossover, we have chosen the ranking method which is picking the best individuals based on objective function value every time,

**Crossover Operator**

We select Pi for cross-over since it has the least objective function value; we also used the one-point cross-over in our approach which involves randomly generating one cross-over point and then swapping clients of the parent chromosomes in order to generate offspring.

Then we calculate the objective function for both offspring's to can equal a new generation.

The offspring of this combination is selected based on an improving objective function, and new offspring's is returned back to the original population and replace with it.

We let this process continue until number of iterations <= 10000 or improvement in objective function value <= 10^-3

**Mutation Operator**

Mutation is applied to each child after crossover. The mutation operator works by selecting randomly one of the clients in the child chromosome and allocating to another place which picked at random and while a crossover fraction considered 0 for this problem then all children are mutation children.

**Replacement population method**

The newly generated child solutions are put back into the original population to replace the less fit members. The average fitness of the population increases as child solutions with better finesses replace the less fit solutions, so it means we used incremental replacement for this problem.

**Population size**

The performance of GA is influenced by the population size. Small populations run the risk of seriously under-covering the solution space, while large populations are computationally intensive [Jaramillo et al, 2002]. we chose a population size equal to n which is equal to the number of clients multiple related depots for this problem.

Population size = Number of clients * 2

The weighted service times for customers are input to the Genetic Algorithms for generating schedules for order delivery to customers. We perform order scheduling for each cluster, which is the results of first step of our study. Genetic algorithms (GA) are ideal for these types of problems where the search space is large and the number of feasible solutions is small. The various steps of GA are presented as follows:

- Set up an initial set of random solutions called population. Each individual in the population is called a chromosome.
- Encode the solution into chromosomes.
- Make crossover; then make mutation.
- Get the offspring, or next generation from above step.
- Decode and evaluate the parent and offspring generation.
- Select current generation and form newer generation.
- Repeat step 2 to step 6 till you get the satisfied solution while meeting the conditions.

We let this process continue either for a pre-allotted time or until we find a solution that fits our objective function. It is also possible, of course, to add further fitness values such as minimizing costs; however, each constraint that we add greatly increases the search space and lowers the number of solutions that are good matches.

**Genetic Algorithm Pseudo-Code**

```
Begin
    For all Depots
    Begin
        Choose initial population (random)
        While (not terminate condition) do
        Begin
            Calculate the objective function for each chromosome
            Calculate Fitness function = 1 /  (total objective function)
            Select chromosomes (Parents) with best fitness values
            Perform crossover to Generate Offspring
            If offspring same as parent chromosome
                Apply mutation operator
            Perform incremental replacement of population by replacing worst parent
    with generated Offspring
        End
    End
End Loop
```

Genetic algorithm is an evolutionary search technique based on the Darwin's principle "Survival of the fittest". The advantage of genetic algorithms is their ability to deal with problems without regarding the inner characteristics, that is, they can handle any kind of objective functions, which makes genetic algorithms very effective at performing global searches.

The limitations include slow speed and requirement of large memory space. Therefore, for developing Genetic algorithms, we need to choose a computer with good CPU and speed.

## 4.3 Vehicle Allocation and Route planning for goods delivery

In this step, we perform vehicle allocation and route planning for goods delivery to customers. The vehicle allocation is based on their capacity to meet order quantities, cost of allocation, emission levels and noise. Using these criteria, we develop a weighted scoring model for vehicle selection. The weighted score for each vehicle allocation solution = $w1$*cost + $w2$*emission + $w3$*noise where $w1$, $w2$ and $w3$ are weights of criteria cost, emission, and noise respectively. The vehicle allocation solution with lowest weighted score is finally selected.

The route planning involves calculation of fastest paths for goods delivery to customers. It takes the allocation and scheduling plan as well as critical routing parameters such as shortest path and vehicle capacities as input. We propose a modified Dijkstra's algorithm for generating fastest paths. The details of original and modified Dijkstra's algorithm are presented as follows.

### 4.3.1 Dijkstra's Algorithm

Dijkstra's algorithm (1959) is a graph search algorithm that solves the single-source shortest path problem for a graph with nonnegative edge path costs, producing a shortest path tree. Dijkstra's algorithm is often used in routing and as a subroutine in other graph algorithms (Cormen at al. 2001).

**Example:**

Let us consider the graph of Figure 4.5. The goal is to find least cost path using Dijkstra's Algorithm.

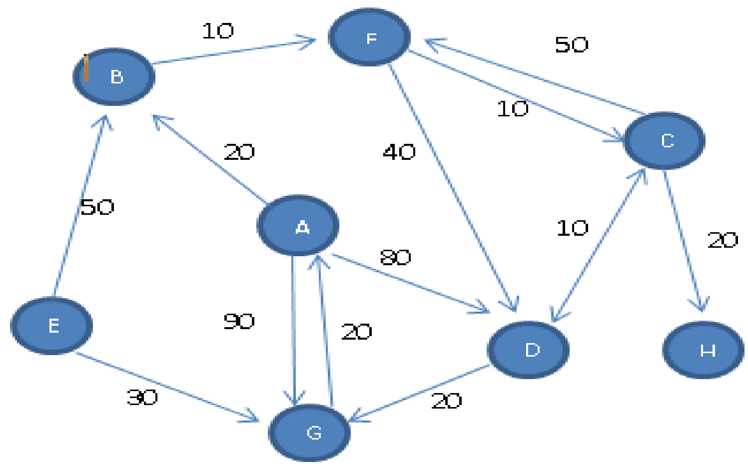



Figure 4.5 Test network for Dijkstra's Algorithm

Based on the Dijkstra's algorithm, we find the shortest paths from a single source node to all other nodes in a weighted, directed graph. All weights must be nonnegative. We want to find shortest path between node A and node G. Table 4.1 presents the intermediate steps of Dijkstra's algorithm and associated distances.

| From → A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|
| 1 → A | 20 | - | 80 | - | - | 90 | - |
| 2 → B | | - | 70 | - | 30 | 90 | - |
| 3 → F | - | 40 | 70 | - | - | 90 | - |
| 4 → C | - | - | 50 | - | - | 90 | 60 |
| 5 → D | - | - | - | - | - | 70 | 60 |
| 6 → G | - | - | - | - | - | 70 | - |

**Table 4.1: Dijkstra's algorithm steps**

So the resulting route is: A → B → F → C → D → G assuming A is the origin and G is the destination. The path length is 70.

### 4.3.2 Modified Dijkstra's Algorithm

The Dijkstra's algorithm finds the shortest path between any given origin-destination pair. In order to adapt it with respect to city traffic conditions, congestion, and access-timing regulations imposed by municipal administrations for our problem, we will modify it and calculate fastest paths instead of shortest distance. The fastest path will be calculated using the weighted distance = $w1$*Travel distance + $w2$*Congestion Delay time + $w3$*Access Delay time where $w1$, $w2$ and $w3$ represent the weights of criteria Travel Distance, Congestion Delay and Access Delay respectively.

### Mathematical Modeling Approach

A goods distribution planning system can be formulated as a mathematical programming problem, defined by an objective function, and a set of constraints to describe the structure of the problem in mathematical ways. The objective function of this kind of problem is a non-linear function, where it is difficult to achieve the optimal solution by mathematical approach, but for this study we are trying to minimize the total goods distribution distance of overall trucks which is as follows:

### Client Allocation Formula

According to Nearest Neighborhood approach, we allocate each customer to its nearest depot based on the shortest distance. Given the two points (*x1, y1*) and (*x2, y2*), the distance between these points is given by the formula:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

The maximum allowed number of clients for each depot is given by:

$$w = \frac{m}{n}$$

Where *m* is the total number of clients and *n* is the total number of depots.

*m* = number of clients

*n* = number of depots

*D(i,j)* = distance between client i and depot j

*n(i)* = number of allocated client to depot j

$$\boldsymbol{Minimize} \quad \sum D(i,j)$$

subject to: *n(i) = w*

where, *w* = maximum allowed number of clients for each depot

**Order Scheduling Formula**

$T_{ij}$ total transit time (minutes) between depot *i* and customer *j*

$t_{ip}$ average time (minutes) for packing *i* th order

$t_{il}$ average loading time (minutes) for $i$ th order

$t_{it}$ average access time (minutes) to transportation facilities for depot $i$

$x_{ti}$ parameter for the availability of depot $i$ at time $t$

Total transit time is the sum of the average delivery time between the customer and the depots ($t_{ij}$), transportation facility access time ($t_{ik}$), and the average access time between depot and the supplier ($t_{il}$).

So, the objective function for the order scheduling formula is written as:

$$Minimize \quad T_{ij} = \left(\sum t_{ip} + \sum t_{il} + \sum t_{it}\right)\left(\sum x_{ti}\right)$$

**Routing Formula**

*Notations:*

$i$ = Job that is assigned to truck; $i \in \{1,2,3,\ldots, n\}$

$l$ = Position that job occupied in a tour; $l \in \{1,2,3,\ldots, m\}$

$k$ = Truck number; $k \in \{1,2,\ldots, m\}$

$m$ = Number of truck;

$oi$ = Order from customer i

$n$ = Actual number of locations; $n \in \{23\}$

$r$ = Upper bound of number of locations visited daily

$d_{i,j}$ = Distance between node $i$ to node $j$

$w_i$ = Weight of order for $i$ (in kgs)

$W$ = Truck capacity

Then,

Total number of jobs (dummy and non-dummy) = $T_n$

The decision variables:

$x_{i,k}$ = 1; if node $i$ assigned to truck $k$

$x_{i,k}$ = 0; otherwise

$y_{i,l,k}$ = 1; if node $i$ occupies position $l$ in the tour for truck $k$

= 0; otherwise

$$Min \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{l=1}^{m-1}\sum_{k=1}^{m} d_{i,j} y_{i,l,k+1} y_{j,l+1,k} + \sum_{i=1}^{n}\sum_{k=1}^{m} d_{0,j} y_{i,r,k} + \sum_{i=1}^{n}\sum_{k=1}^{m} d_{0,i} y_{i,1,k}$$

- This formula is subject to the load of all trucks which should not exceed its capacity

$$\sum_{i=1}^{n}\sum_{l=1}^{r} w_i\, y_{i,1,k} \le W; \qquad for\ 1 \le K \le m$$

- We can assign the job $i$ to one and only one truck at a time

$$\sum_{k=1}^{m} x_{i,k} = 1; \qquad for\ 1 \le i \le n$$

- For each job $i$ which is assigned to truck $k$ it takes one position 1 in the tour that truck $k$ performs

$$\sum_{i=1}^{n}\sum_{k=1}^{m} y_{i,1,k} = 1; \qquad for\ 1 \le l \le r$$

- Every job $i$ takes only one position in the tour which is performed by truck $k$

$$\sum_{i=1}^{m}\sum_{k=1}^{m} y_{i,1,k} = 1 ; \qquad\qquad for\ 1 \leq i \leq n$$

- Job $i$ takes one position in the tour which is performed by truck $k$ if job $i$ is assigned to truck $k$

$$\sum_{r=1}^{m} y_{i,1,k} \leq x_{i,k} ; \qquad\qquad for\ 1 \leq i \leq n\ and\ 1 \leq k \leq m$$

# Chapter 5:

# Numerical Study

## 5.1 Six-Customer, 2-Depot Problem

Let us consider a distribution network containing 2 logistical facilities (depots) and 6 customers. The information on minimum travel time (MTT), access regulation delay (ARD), time regulation delay (TRD), and congestion delay (CD) between the various customers and the depots is provided in Table 5.1. The weights of the criteria shown in Table 5.1 are presented in Table 5.2.

| **D1** | | | | | | |
|---|---|---|---|---|---|---|
| **Criteria** | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** |
| **MTT** | 13.4 | 15.3 | 7.5 | 6.7 | 16.4 | 5.7 |
| **ARD** | 4.9 | 4.5 | 2.5 | 3.1 | 5.1 | 2.9 |
| **TRD** | 10.9 | 11 | 3.7 | 3.5 | 12.2 | 3.4 |
| **CD** | 9.8 | 10.4 | 4.8 | 4.3 | 8.7 | 4.3 |
| ***Weighted Travel Time*** | 12.2 | 14.1 | 5 | 4.2 | 15.7 | 3.6 |
| D2 | | | | | | |
| **Dist** | 9.3 | 8.7 | 8.7 | 16.3 | 6.4 | 14.7 |
| **MTT** | 4.8 | 4.5 | 4.7 | 4.5 | 2.1 | 5.8 |
| **TRD** | 5.9 | 4.3 | 3.7 | 11 | 2.2 | 11.8 |
| **CD** | 8.6 | 10.4 | 11.8 | 12.4 | 3.4 | 9.8 |
| ***Weighted Travel Time*** | 9.2 | 9.8 | 9.9 | 15.3 | 5.7 | 11.4 |

**Table 5.1: Allocation criteria values for the 6 customer problem**

| Criteria | Weight |
|---|---|
| Minimum Travel Time | 60% |
| Access regulation delay | 5% |
| Time regulation delay | 5% |
| Congestion delay | 30% |
| *Weighted Travel Time* | 100% |

**Table 5.2: Allocation criteria with weights**

The weighted travel time for the six customers computed using the information presented in Tables 5.1-5.2 is presented in Table 5.3.

| | D1 | D2 | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|---|---|
| **D1** | 0 | | | | | | | |
| **D2** | 14.9 | 0 | | | | | | |
| **C1** | 9.2 | 12.2 | 0 | | | | | |
| **C2** | 14.1 | 9.8 | 2 | 0 | | | | |
| **C3** | 5 | 9.9 | 9.2 | 11.2 | 0 | | | |
| **C4** | 7.2 | 15.3 | 15 | 17 | 6.1 | 0 | | |
| **C5** | 15.7 | 14.7 | 5.4 | 5 | 11.4 | 17.4 | 0 | |
| **C6** | 3.6 | 11.4 | 9 | 11 | 2 | 6.1 | 12.1 | 0 |

**Table 5.3: Weighted *Travel Time* for 6-customer problem**

### 5.1.1 Customer Allocation

We generate the primary solutions based on finding nearest neighbourhood for each depot and also we considering the balance allocation then we select the solution which returns lowest value as a initial solution

D1: C1C6C4 (Weighted Travel Time = 20)

D2: C3C5C2 (Weighted Travel Time = 34.4)

Overall objective function value so far for initial solution is D1C1C6C4D1D2C3C5C2D2=20+34.4 = 54.4. The initial solution is now input into the Tabu Search for further improving the solution quality. Let us generate a neighbourhood solution

**Neighbourhood**: A neighbourhood for this problem is defined as any other solution that is obtained by an exchange of any two clients in the solution where a balance allocation is considered. This always guarantees that any neighbourhood to a feasible solution is always a feasible solution. If we considering the distance between each client and depot, at each iteration the neighbourhood with the best objective value (minimum distance) is selected.

| | | | |
|---|---|---|---|
| Generating neighbour | D1C1C6C4D1 | ⟶ | D1C1C3C4D1 |
| | D2C2C3C5D2 | ⟶ | D2C2C6C5D2 |

New Neighbourhood = {(D1, C1,C3,C4), (D2, C2,C6,C5)}

D1C1C3C4D1D2C2C6C5D2 =57.3

The new neighbourhood solutions are generated as follows :

D1C1C3C4D1D2C2C6C5D2 =57.3 (S1)
D1C1C5C4D1D2C3C2C6D2=63.2 (S2)
D1C1C5C6D1D2C2C3C4D2=63.5 (S3)
D1C2C5C6D1D2C1C4C3D2=70.8 (S4)
D1C3C4C6D1D2C1C5C2D2=52.5 (S5)
D1C4C3C2D1D2 C1C5C6 D2=64.6 (S6)

After a move that exchanges the positions of element C6 and C3 in a sequence for S1 solution, , we would like to prevent elements C6 and C3 from exchanging positions in the next Tabu Tenure iterations

Tabu activation rule: move (Ci ↔ Cj) is tabu if both Ci and Cj are tabu-active

The C6-C3 in solution S1 is also can added to the tabu list for avoid repetitive solutions if the new solution is better than the previous one and is not present in the tabu list and we continue this method for all solutions.

**Tabu list**

Tabu list with elements (D1C3-D2C6, D3C9-D4C12, D5C15-D6C18)

Consequently we are able to generate different neighbourhood from current solution through dropping and adding clients to current solution, we generate solutions in the neighbourhood of S5 and repeat the whole process again for updating best solution at every iteration.

In the neighbourhood, the best feasible solution emerges to be (S5) with the least objective function (travel time) value = 52.5 The difference between the initial and the current solution (S5) is given by 2.1 (value has actually reduced):

Can-now= D1C3C4C6D1D2 C1C5C2 D2=5+7.2+3.6+12.2+14.7+9.8=52.5

Δf= D1C1C6C4D1D2C3C5C2D2- D1C3C4C6D1D2 C1C5C2 D2=54.4-52.5=2.1

We exchange customers C4 and C5 in (S5) and the new allocation (S6) is given by.

D1C3C5C1D1D2 C6C4C2 D2=5+15.7+9.2+11.4+15.3+9.8=66.4 (S6)

Δf= D1C3C5C1D1D2C6C4C2D2- D1C3C4C6D1D2C1C5C2D2=66.4-52.5=13.9

It can be seen that the objective function value has increased. Therefore, (S6) will be added to the tabu list by replacing the second worst objective function solution (S1). Now, we exchange customers C6 and C2 in (S6) to generate the new solution.

D1C3C4C2D1D2C5C1C6D2=5+7.2+14.1+14.7+12.2+11.4=64.6 (S7)

Δf= D1C3C4C2D1D2C5C1C6D2- D1C3C4C6D1D2 C1C5C2 D2=64.6-52.5=12.1

Now we exchange between C3 and C5:

D1C1C2C5D1D2C4C3C6D2=9.2+14.1+15.7+15.3+9.9+11.4=75.6 (S8)

Δf= D1C1C2C5D1D2C4C3C6D2- D1C3C4C6D1D2 C1C5C2 D2=75.6-52.5=23.1

As, (S8) has the worst objective function value, it will not be put in the tabu list. Now, we use the 3 elements change method, and generate feasible solutions (neighbourhood) by putting C1C2C5 after C6:

**D1C4C3C6 D 1D2C1C2C5D2=5+7.2+3.6+12.2+9.8+14.7=52.5 (S9)**

Δf= D1 C 4C3C6 D 1D2C1C2C5D2- D1C3C4C6D1D2 C1C5C2 D2=52.5-52.5=0 (N)

Since, M has the least objective function value so far, we renew tabu list (I,E,C,B, H).

We continue computations in this way and find that the newer values of objective function, we could use (S9) as the best solution. In fact, it is the best actual solution from beginning.

**Short-Term Memory:** we considering the short-term memory for this problem and it is the list of recent solutions. If a potential solution appears on this list, it cannot be revisited until it reaches an expiration point, and expiration point for this problem is termination of algorithm.

STM List = (S0,S1,S2,S3,..,S9)

**Aspiration Criteria**: We define the aspiration criteria as a solution involving tabu move that has better objective value than best known answer, then the tabu status is disregarded.

An aspiration criteria is used to overrule the tabu restriction, therefore we can consider the attractive unvisited solution as well

**Diversification**: some times, the process may get trapped in a space of local optimum. To allow the process to search other parts of the solution space, it is required to diversify the search process, driving it into new regions. This is implemented in the this problem with swaps a client with different depots which means we can swaps C6 from Depots 1 to C3 from Depots 2.

C6D1→ C3D2

**Termination criteria**: The algorithm terminates if it meets any one of the following criteria:

a. It reaches a 8,000 iterations.

b. The objective function is improved with 15% improvement to compare with initial solution.

c. There is no improvement in the solution for last 8,000 iterations.

This process continues until maximum number of iterations have been reached or very minimal improvement in objective function value (say <= $10^{-5}$) is observed.

The results of customer allocation obtained using the Nearest Neighbor and Tabu Search approach are presented in following.

**D1 → C4C3C6**
**D2 → C1C2C5**

### 5.1.2 Scheduling

The order scheduling of customers in the clusters obtained from previous step is performed using Genetic algorithm. Table 5.4 presents the order details of the customers.

| Client | Depot | Order |
|---|---|---|
| C1 | D2 | 4000 |
| C5 | D2 | 1000 |
| C3 | D1 | 2500 |
| C4 | D1 | 200 |
| C2 | D2 | 2000 |
| C6 | D1 | 1500 |

**Table 5.4: Order Quantity for six customer problem**

Table 5.5 presents the information required for scheduling of customers C1 to C6. We are assuming that these orders have been requested during a common time window. In case, the customers have different time windows then we will first group the customers based on their preferred time windows and then schedule each group in a similar way. The objective is to minimize the total service time and distribution costs (weighted score of different criteria as indicated in last row Table 5.5) for all clients.

| Criteria | Weight | C1-D2 | C2-D2 | C3-D1 | C4-D1 | C5-D2 | C6-D1 |
|---|---|---|---|---|---|---|---|
| **Loading Time** | 10% | 50 | 50 | 50 | 50 | 50 | 50 |
| **Transit time** | 30% | 70 | 90 | 50 | 75 | 80 | 60 |
| **Historical Delay Time(city)** | 20% | 60 | 70 | 80 | 50 | 60 | 40 |
| **Packing Time** | 15% | 50 | 60 | 40 | 50 | 40 | 30 |
| **Access Time to Facility** | 10% | 0 | 10 | 10 | 90 | 0 | 10 |
| **Unloading Time** | 15% | 90 | 50 | 60 | 20 | 10 | 70 |
| ***Weighted Service Time (Min)*** | 100% | 58 | 64 | 52.5 | 57 | 48.5 | 47 |

**Table 5.5: Order scheduling information for six customer problem**

The weighted Service Time presented in last row of Table 5.5 is calculated using the weighted scoring model for customers C1-C6 as follows:

C1= (10*50)+(30*70)+(20*60)+(15*50)+(10*0)+(15*90) = 5800
C2= (10*50)+(30*90)+(20*70)+(15*60)+(10*10)+(15*50) = 6400
C3= (10*50)+(30*50)+(20*80)+(15*40)+(10*10)+(15*60) = 5250
C4= (10*50)+(30*75)+(20*50)+(15*50)+(10*90)+(15*20) = 5700
C5= (10*50)+(30*80)+(20*60)+(15*40)+(10*0)+(15*10) = 4850
C6= (10*50)+(30*60)+(20*40)+(15*30)+(10*10)+(15*70) = 4700

From step 1, we know that the following customers are allocated to depot 1 and 2.

**D1 → C4C3C6**
**D2 → C1C2C5**

We will use Genetic Algorithm to schedule the customer orders. Initially, we will generate a set of solutions for depot D1:

Function:

S1= D1C4C3C6D1
S2= D1C6C4C3D1
S3= D1C4C6C3D1
S4= D1C3C4C6D1
S5= D1C3C6C4D1
S6= D1C6C3C4D1

FS1= D1C4C3C6D1 =193.5
FS2= D1C6C4C3D1 =205.5
FS3= D1C4C6C3D1 =198.5
FS4= D1C3C4C6D1 =205.5
FS5= D1C3C6C4D1 =198.5
FS6= D1C6C3C4D1 =193.5

The initial population for depots 1 consists of six chromosomes P1, P2 ,P3 ,P4,P5,P6 generated at random.

| | Solution String | | | | | Objective Function |
|---|---|---|---|---|---|---|
| P1 | 1 | 4 | 3 | 6 | 1 | 193.5 |
| P2 | 1 | 6 | 4 | 3 | 1 | 205.5 |
| P3 | 1 | 4 | 6 | 3 | 1 | 198.5 |
| P4 | 1 | 3 | 4 | 6 | 1 | 205.5 |
| P5 | 1 | 3 | 6 | 4 | 1 | 198.5 |
| P6 | 1 | 6 | 3 | 4 | 1 | 193.5 |

We take this initial population and cross it, combining genomes along with a small amount of randomness (mutation).

**Fitness function**

Since, scheduling for this problem is minimizing the total travel time for delivering the orders, we consider below fitness function, where f(x) calculates total weighted service time as an objective function of the schedule.

$$F(x) = \frac{1}{f(x)}$$

**Parents Selection Procedure**

To select the parents for crossover, we have chosen the ranking method which is picking the best individuals based on objective function value every time,

P1< P2 & P1< P3 & P1< P4 & P1< P5 then P1 is selected.

**Crossover Operator**

We select P1 for cross-over since it has the least objective function value; we also used the one-point cross-over in our approach which involves randomly generating one cross-over point and then swapping clients of the parent chromosomes in order to generate offspring.

| | | | | | |
|---|---|---|---|---|---|
| *O1* | *D1* | *C3* | *C4* | *C6* | *D1* |

*And*

| | | | | | |
|---|---|---|---|---|---|
| *O2* | *D1* | *C6* | *C3* | *C4* | *D1* |

We calculate the objective function for both offspring's to can equal a new generation.

FO1= D1C3C4C6D1=205.5

FO2=D1C6C3C4D1=193.5

The offspring of this combination is selected based on an improving objective function, so the offspring FO2 is the same as parent chromosomes therefore, the new offsprings O2 can be returned back to the original population and replace with P1.

So for Iteration number two we have:

S1= D1C6C3C4D1
S2= D1C6C4C3D1
S3= D1C4C6C3D1
S4= D1C3C4C6D1
S5= D1C3C6C4D1
S6= D1C6C3C4D1

We let this process continue for each depots until number of iterations <= 5000 or improvement in objective function value <= 10^-3

**Mutation Operator**

Mutation is applied to each child after crossover. The mutation operator works by selecting randomly one of the clients in the child chromosome and allocating to another place which picked at random and while a crossover fraction considered 0 for this problem then all children are mutation children.

| | | | |
|---|---|---|---|
| *O1* | *C4* | $\longrightarrow$ | *C3* |
| *O2* | *C4* | $\longrightarrow$ | *C6* |

**Replacement population method**

The newly generated child solutions are put back into the original population to replace the less fit members. The average fitness of the population increases as child solutions with better finesses replace the less fit solutions, so it means we used incremental replacement for this problem.

**Population size**

The performance of GA is influenced by the population size. Small populations run the risk of seriously under-covering the solution space, while large populations are computationally intensive [Jaramillo et al, 2002]. we chose a population size equal to n which is equal to the number of clients multiple related depots  for this problem.

Population size = Number of clients * 2 (begin and end depot) = 6

Therefore, the final order schedule for depot 1 using the proposed GA approach is C6C3C4 and for depot 2 is C2C5C1.

### 5.1.3 Vehicle allocation and Routing

Table 5.6 presents the different vehicle types, their capacities, emission factors and noise.

| No | Type | Quantity (truck) | Capacity (ton) | Operating Cost (Dollars per day) | Emission Factor | Noise |
|---|---|---|---|---|---|---|
| 1 | Small Size Truck (S) | 6 | 1 | 350 | Low (15) | Low (10) |
| 2 | Big Size Truck (B) | 3 | 5.5 | 600 | High (60) | High (35) |
| 3 | Medium Truck (M) | 4 | 3 | 500 | Medium(35) | Medium (20) |

**Table 5.6: Vehicle Details for six customer problem**

For depots 1 and 2, we have the following scheduled orders:

Depot 1 = C6C2C3 (Order quantity = 6000) and Depot 2 = C4C5C1 (Order quantity = 5200)

To serve order quantities for customers of depots 1 and 2, two solutions for vehicle allocations are possible.

Solution 1: Using 2 medium size truck (Capacity = 3000+3000 = 6000)

Solution 2: Using 1 big and 1 small truck (Capacity = 5500+1000 = 6500)

Now, we will evaluate these two solutions using weighted scoring method. Table 5.7 presents the evaluation results using the cost, emissions and noise criteria.

| | Weight | Solution 1 (2M) | Solution2 (1 B,1 S) |
|---|---|---|---|
| **Cost** | 70% | 1000 | 950 |
| **Emission** | 20% | 70 | 75 |
| **Noise** | 10% | 40 | 45 |
| **Weight** | 100% | 718 | 684.5 |

**Table 5.7: Solution weight scoring for 6 customer problem**

Since, the weighted score of solution 2 is less than solution 1, so we choose solution number 2 for vehicle allocation.

Now, we will generate shortest path for the vehicles (solution 2) using Modified Dijkstra's algorithm to serve the clients of depot 1. Table 5.8 represents the weighted distance used in modified Dijkstra's algorithm for planning shortest paths for customers of depot 1.

| | D1 | C6 | C3 | C4 |
|---|---|---|---|---|
| **D1** | **0** | **3.6** | **14** | **5** |
| **C6** | **3.6** | **0** | **11** | **2** |
| **C3** | **14** | **11** | **0** | **11.2** |
| **C4** | **5** | **2** | **11.2** | **0** |

**Table 5.8: Distance data for depot 1 (or group A)**

Figure 5.1 presents the test network for depot 1 (or group A). Using modified Dijkstra's algorithm, the fastest path for depot 1 (group A) is: A → C6 → C3 → C4→ A . Likewise, the fastest path for depot 2 (group B) is calculated. The solution is given by B → C2 → C5→ C1→ B.

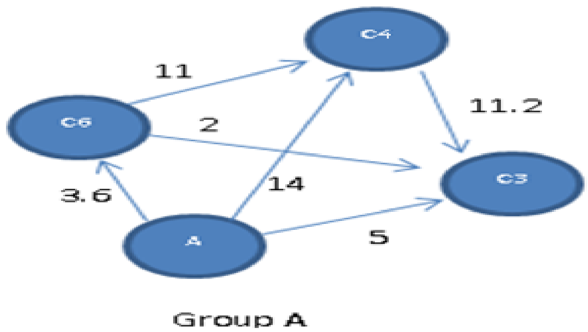



**Figure 5.1: Test Network for group A**

The allocation, scheduling and routing results for the 6-customer problem are summarized In Table 5.9. It can be seen that the objective function has improved (or weighted travel time reduced) for the allocation and scheduling problems. For the routing problem, the objective function remains unchanged.

| Problem Type | Initial solution | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| Allocation (NN-TS Approach) | D1 → C1C6C4 | 20 | 54.4 | D1 → C4C3C6 | 22.7 | 52.9 |
| | D2 → C3C5C2 | 34.4 | | D2 → C1C2C5 | 30.2 | |
| Scheduling (GA Approach) | D1 → C4C3C6 → D1 | 30.9 | 78.2 | S1 → D1C6C3C4D1 | 30.8 | 78.1 |
| | D2 → C1C2C5 → D2 | 47.3 | | S1 → D2C2C5C1D2 | 47.3 | |
| Routing (Modified Dijkstra's) | S1 → D1C6C3C4D1 | 30.8 | 78.1 | R1 → D1→ C6 → C3 → C4 → D1 | 30.8 | 78.1 |
| | S1 → D2C2C5C1D2 | 47.3 | | R1 → D2 → C2 → C5→ C1→ D2 | 47.3 | |

**Table 5.9: Solution summary for 6-customer problem**

## 5.2 Model Verification

To verify the model results, we tested our model under three different problem instances. The first problem is same as present in section 5.1. The second problem involves 21 customers and 7 depots. The third problem involves 50 customers and 5 depots. We performed Client allocation, Order Scheduling and Vehicle Routing for these problems using the TS-NN, GA, Weighted Scoring and Modified Dijkstra's algorithm.

### 5.2.1. Twenty One - Customers, Seven - Depots problem

Table 5.10 presents the weighted travel times, customer demands and the capacities of the seven depots. The weights of the criteria Minimum travel time, Access Regulation Delay, Time Regulation Delay are same as in Table 5.2.

| | **Depots** | | | | | | | **demand** |
|---|---|---|---|---|---|---|---|---|
| | D1 | D2 | D3 | D4 | D5 | D6 | D7 | |
| **C1** | 3.4 | 3.74 | 4.2 | 3.2 | 3.3 | 4.8 | 2.1 | 120 |
| **C2** | 3.10 | 3.28 | 3.3 | 2.7 | 4.0 | 3.1 | 5.8 | 200 |
| **C3** | 3. 8 | 3. 4 | 3.2 | 2.9 | 3.0 | 2.4 | 4.8 | 80 |
| **C4** | 3.5 | 3.6 | 3.5 | 4.9 | 3.6 | 2.5 | 4.9 | 110 |
| **C5** | 3.7 | 3.0 | 3.2 | 4.6 | 2.0 | 3.2 | 4.6 | 130 |
| **C6** | 3.6 | 3.7 | 3.6 | 4.7 | 3.7 | 3.8 | 4.7 | 90 |
| **C7** | 2.88 | 2.97 | 7.3 | 3.31 | 3.5 | 3.6 | 4.5 | 140 |
| **C8** | 2.5 | 2.9 | 3.0 | 2.83 | 2.7 | 3.0 | 3.2 | 170 |
| **C9** | 2.6 | 2.7 | 4.82 | 3.2 | 3.6 | 3.7 | 10.8 | 90 |
| **C10** | 5.8 | 2.8 | 3.2 | 5.3 | 4.74 | 4.2 | 6.1 | 115 |
| **C11** | 3.1 | 2.9 | 6.7 | 3.0 | 3.28 | 3.3 | 4.4 | 100 |
| **C12** | 2.4 | 2. 7 | 2.9 | 5.0 | 3.24 | 6.5 | 2.0 | 125 |
| **C13** | 3.5 | 3.30 | 3.5 | 3.6 | 9.04 | 2.8 | 4.5 | 85 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **C14** | 4.2 | 2.96 | 2.7 | 1.0 | 3.03 | 3.0 | 2.3 | 180 |
| **C15** | 3.1 | 3.2 | 2.6 | 2.74 | 2.82 | 3.7 | 4.1 | 130 |
| **C16** | 3.2 | 4.3 | 2.8 | 2.88 | 3.2 | 3.3 | 2.8 | 95 |
| **C17** | 2.7 | 5.0 | 3.1 | 2.92 | 5.7 | 6.0 | 3.1 | 175 |
| **C18** | 5.9 | 3.0 | 2.4 | 2.47 | 2.9 | 3.0 | 2.4 | 150 |
| **C19** | 3.5 | 1.6 | 3.5 | 1.30 | 3.5 | 3.6 | 7.5 | 190 |
| **C20** | 2.7 | 3.0 | 5.2 | 2.96 | 2.7 | 3.0 | 1.2 | 95 |
| **C21** | 2.6 | 3.7 | 4.8 | 3.28 | 3.6 | 6.7 | 3.8 | 160 |
| **Capacity** | 800 | 800 | 1100 | 1000 | 700 | 1100 | 900 | |

**Table 5.10 Weighted travel times, capacity and demand data for 21 customer problem**

For this sample we consider 7 logistics depots D1,D2,D3,D4,D5,D6,D7 and 21 customers C1, C2, …, C21 respectively. We generate the primary solutions based on finding nearest neighborhood for each depot and also we considering the balance allocation.

S(A)=(D1,C1,C2,C3,D2,C4,C5,C6,D3,C7,C8,C9,D4,C10,C11,C12,D5,C13,C14,C15,D6,C16,C17,C18,D7,C19,C20,C21) = 84.91

S(B)=(D1,C1,C2,C3,D2,C7,C8,C18,D3,C19,C20,C21,D4,C4,C5,C6,D5,C13,C14,C12,D6,C16,C17,C18,D7,C9,C10,C11) = 92.68

S(C)=(D1,C3,C15,C14,D2,C16,C18,C19,D3,C8,C20,C21,D4,C4,C5,C6,D5,C13,C2,C7,D6,C1,C17,C12,D7,C9,C10,C11) = 98.54

S(D)=(D1,C3,C10,C18,D2,C4,C17,C21,D3,C7,C20,C11,D4,C12,C5,C2,D5,C13,C2,C19,D6,C1,C8,C16,D7,C9,C14,C15) = 102.07

Then we check the feasibility for this generated solution and then we select the solution which returns lowest value as a initial solution .

S0 = {(D1, C1,C2,C3),(D2, C4,C5,C6) ,(D3, C7,C8,C9),(D4, C10,C11,C12) ),(D5, C13,C14,C15) ,(D6, C16,C17,C18) ,(D7, C19,C20,C21))}

D1C1C2C3D1D2C4C5C6D2D3C7C8C9D3D4C10C11C12D4D5C13C14C15D5D6C16C17C18 D6D7C19C20C21D7= 84.91

Overall objective function value so far for initial solution is = 84.91.

Let us generate a neighboring solution

**Neighbourhood**: A neighbourhood for this problem is defined as any other solution that is obtained by an exchange of any two clients in the solution where a balance allocation is considered. This always guarantees that any neighbourhood to a feasible solution is always a feasible solution. If we considering the distance between each client and depot, at each iteration the neighbourhood with the best objective value (minimum distance) is selected.

| | | | |
|---|---|---|---|
| Generating neighbor | D1C1C2C3D1 | $\longrightarrow$ | D1C1C2C6D1 |
| | D2C4C5C6D2 | $\longrightarrow$ | D2C4C5C3D2 |
| | D3C7C8C9D3 | $\longrightarrow$ | D3C7C8C12 |
| | D4C10C11C12D4 | $\longrightarrow$ | D4C10C11C9 |
| | D5C13C14C15D5 | $\longrightarrow$ | D5C13C14C18 |
| | D6C16C17C18D6 | $\longrightarrow$ | D6C16C17C15 |
| | D7C19C20C21D7 | $\longrightarrow$ | D7C19C20C21 |

New Neighbourhood S1 = {(D1, C1,C2,C6), (D2, C4,C5,C3) ,(D3, C7,C8,C12),(D4, C10,C11,C9) ,(D5, C13,C14,C18),(D6, C16,C17,C15) ,(D7, C19,C20,C21))} .

S1 = {(D1, C1,C2,C6), (D2, C4,C5,C3) ,(D3, C7,C8,C12),(D4, C10,C11,C9) ,(D5, C13,C14,C18),(D6, C16,C17,C15) ,(D7, C19,C20,C21))} .

D1C1C2C6D1D2C4C5C3D2D3C7C8C12D3D4C10C11C9D4D5C13C14C18D5D6C16C17C15 D6D7C19C20C21D7 =81.87

After a move that exchanges the positions of element C3,C9,C15 and C6,C12,C18 in a sequence for S1 solution, , we would like to prevent elements C3,C9,C15 and C6,C12,C18 from exchanging positions in the next Tabu Tenure iterations

Tabu activation rule: move (Ci ↔ Cj) is tabu if both Ci and Cj are tabu-active

The C3-C6 , C9-C12, C15-C18 in solution S1 is also added to the tabu list for avoid repetitive solutions from entering into the tabu list.

Since, the new solution is better than the previous one and is not present in the tabu list the new solution is accepted and updated as the best solution.

{D1(C1,C2,C6),D2(C4,C5,C3),D3(C7,C8,C12),D4(C10,C11,C9),D5(C13,C14,C18),
D6(C16,C17,C15),D7(C19,C20,C21)}

**Tabu list**

Let us initiate the Tabu list with elements (D1C3-D2C6, D3C9-D4C12, D5C15-D6C18)

Consequently we are able to generate different neighborhood from current solution through dropping and adding clients to current solution, we generate solutions in the neighborhood of S1 and repeat the whole process again for updating best solution at every iteration.

A tabu move will be considered only if, it would result in an improving objective function than the initial solution found previously.

New Neighbourhood S2 = {(D1, C1,C2,C4), (D2, C6,C8,C3) ,(D3, C7,C5,C12),(D4, C18,C11,C9) ,(D5, C13,C14,C10),(D6, C21,C17,C15) ,(D7, C19,C20,C16))} .

D1C1C2C4D1D2C6C8C3D2D3C7C5C12D3D4C18C1C9D4D5C13C14C10D5D6C21C17C15 D6D7C19C20C16D7 =83.38

Since, the solution S2 is not improved than the previous one so the new solution is not accepted .

To preventing cycling and re-visiting previously visited solution tabu move restrictions are employed. In our implementation we classify a solution obtained by swapping the clients as a tabu if it corresponds to the same swapping which was swapped in an accepted solution.

**Short-Term Memory:** we considering the short-term memory for this problem and it is the list of recent solutions. If a potential solution appears on this list, it cannot be revisited until it reaches an expiration point, and expiration point for this problem is termination of algorithm.

STM List = (S0,S1,S2)

**Aspiration Criteria**: We define the aspiration criteria as a solution involving tabu move that has better objective value than best known answer, then the tabu status is disregarded.

An aspiration criteria is used to overrule the tabu restriction, therefore we can consider the attractive unvisited solution as well

**Diversification**: some times, the process may get trapped in a space of local optimum. To allow the process to search other parts of the solution space, it is required to diversify the search process, driving it into new regions. This is implemented in the this problem with swaps a client with different depots which means we can swaps C1 from Depots 1 to C20 from Depots 7.

C1D1→ C20D7

**Termination criteria**: The algorithm terminates if it meets any one of the following criteria:

a. It reaches a 100,000 iterations.

b. The objective function is improved with 15% improvement to compare with initial solution.

c. There is no improvement in the solution for last 100,000 iterations.

This process continues until maximum number of iterations have been reached or very minimal improvement in objective function value (say <= $10^{-5}$) is observed.

The results of customer allocation obtained using the Nearest Neighbor and Tabu Search approach are presented in Table 5.11. It can be seen that the objective function value has improved with respect to the initial solution.

| Depots | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| D1 | C1,C2,C3 | 6.5 | 85 | D1 → C6C7C8 | 8.98 | 53.38 |
| D2 | C4,C5,C6 | 10.3 | | D2 → 10C11C9 | 8.4 | |
| D3 | C7,C8,C9 | 15.12 | | D3 → C15,C16,C17 | 8.5 | |
| D4 | C10,C11,C12 | 13.3 | | D4 → C2,C14,C19 | 5 | |
| D5 | C13,C14,C15 | 14.98 | | D5 → C20,C5,C21 | 8.3 | |
| D6 | C16,C17,C18 | 12.3 | | D6 → C13,C3,C4 | 7.7 | |
| D7 | C19,C20,C21 | 12.5 | | D7 → C1,C12,C18 | 6.5 | |

**Table 5.11: Allocation Results for the 21 customer problem**

Table 5.12 presents the customer order information for the allocated clients.

| Depot Id | Client Id | Order Quantity |
|---|---|---|
| D1 | C6 | 4200 |
| D1 | C7 | 4500 |
| D1 | C8 | 4500 |

**Table 5.12: Order Data for 21-customer problem**

Table 5.13 presents the other information used for scheduling orders of customer clusters obtained from step 1.

| Customers | Criteria | | | | | | |
|---|---|---|---|---|---|---|---|
| | Loading Time | Transit time | Historical Delay Time(city) | Packing Time | Access Time to Facility | Unloading Time | Weighted Client Score |
| | 10% | 30% | 20% | 15% | 10% | 15% | 100% |
| C1-D7 | 50 | 40 | 60 | 40 | 20 | 10 | 3850 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| C2-D4 | 50 | 45 | 30 | 60 | 80 | 30 | 4600 |
| C3-D6 | 40 | 55 | 35 | 75 | 95 | 20 | 5125 |
| C4-D6 | 50 | 25 | 40 | 80 | 60 | 35 | 4375 |
| C5-D5 | 40 | 65 | 55 | 30 | 95 | 15 | 5075 |
| C6-D1 | 60 | 52 | 38 | 86 | 32 | 18 | 4800 |
| C7-D1 | 78 | 24 | 58 | 90 | 34 | 26 | 4740 |
| C8-D1 | 45 | 36 | 72 | 80 | 95 | 15 | 5345 |
| C9-D2 | 12 | 28 | 36 | 92 | 74 | 60 | 4700 |
| C10-D2 | 56 | 88 | 25 | 40 | 80 | 75 | 6225 |
| C11-D2 | 84 | 55 | 65 | 55 | 30 | 80 | 6115 |
| C12-D7 | 12 | 48 | 52 | 38 | 86 | 30 | 4480 |
| C13-D6 | 18 | 42 | 40 | 60 | 30 | 86 | 4730 |
| C14-D4 | 94 | 25 | 40 | 24 | 35 | 90 | 4550 |
| C15-D3 | 57 | 78 | 40 | 36 | 40 | 80 | 6321 |
| C16-D3 | 16 | 45 | 40 | 28 | 55 | 92 | 4653 |
| C17-D3 | 18 | 40 | 40 | 88 | 38 | 40 | 4872 |
| C18-D7 | 30 | 45 | 45 | 55 | 60 | 55 | 3879 |
| C19-D4 | 55 | 55 | 55 | 35 | 75 | 38 | 5423 |
| C20-D5 | 47 | 25 | 25 | 40 | 80 | 60 | 4879 |
| C21-D5 | 80 | 65 | 65 | 55 | 30 | 95 | 5210 |

**Table 5.13: Order scheduling information for 21 customer problem**

In order to solve to our scheduling plan by Genetic Algorithm, two main requirements are to be satisfied: First a string can represent a solution of the solution space, and second an objective function and hence a fitness function which measures the goodness of a solution can be defined.

We generate an initial population by using output of allocation section and each individual in the population is called a chromosome, then take this initial population and cross it, combining genomes along with a small amount of randomness (mutation).

S1= D1C6C7C8D1

S2= D1C7C6C8D1

S3= D1C8C6C7D1

S4= D1C6C8C7D1

S5= D1C7C8C6D1

S6= D1C8C7C6D1

We continue to set up the initial population for all different depots, and then we calculate the objective function based on weight scoring result for each population.

FS1= D1C6C7C8D1=37.3

FS2= D1C7C6C8D1=25.32

FS3= D1C8C6C7D1=32.48

FS4= D1C6C8C7D1=25.32

FS5= D1C7C8C6D1=32.48

FS6= D1C8C7C6D1=37.3

The initial population for depots 1 consists of six chromosomes P1, P2 ,P3 ,P4,P5,P6 generated at random.

| | Solution String | | | | | Objective Function |
|---|---|---|---|---|---|---|
| P1 | 1 | 6 | 7 | 8 | 1 | 37.3 |
| P2 | 1 | 7 | 6 | 8 | 1 | 25.32 |
| P3 | 1 | 8 | 6 | 7 | 1 | 32.48 |
| P4 | 1 | 6 | 8 | 7 | 1 | 37.3 |
| P5 | 1 | 7 | 8 | 6 | 1 | 25.32 |
| P6 | 1 | 8 | 7 | 6 | 1 | 32.48 |

We take this initial population and cross it, combining genomes along with a small amount of randomness (mutation).

**Fitness function**

Since, scheduling for this problem is a minimization in terms of minimizing the total travel time for delivering the orders, we consider below fitness function, where f(x) calculates total travel time or weighted client score value as an objective function of the schedule.

$$F(x) = \frac{1}{f(x)}$$

**Parents Selection Procedure**

To select the parents for crossover, we have chosen the ranking method which is picking the best individuals based on objective function value every time,

P2< P1 & P2< P3 & P2< P4 & P2< P5 & P2< P6    then P2 is selected.

**Crossover Operator**

We select P2 for cross-over since it has the least objective function value; we also used the one-point cross-over in our approach which involves randomly generating one cross-over point and then swapping clients of the parent chromosomes in order to generate offspring.

| | | | | | |
|---|---|---|---|---|---|
| *O1* | *D1* | *C7* | *C8* | *C6* | *D1* |

*And*

| | | | | | |
|---|---|---|---|---|---|
| *O2* | *D1* | *C8* | *C6* | *C7* | *D1* |

We calculate the objective function for both offspring's to can equal a new generation.

FO1= D1C7C8D1C6=25.3

FO2=D1C7D1C6C8=32.48

The offspring of this combination is selected based on an improving objective function, so the offspring FO1 is lower than the parent chromosomes therefore, the new offsprings O1 is returned back to the original population and replace with P2.

We let this process continue until number of iterations <= 5000 or improvement in objective function value <= 10^-3

**Mutation Operator**

Mutation is applied to each child after crossover. The mutation operator works by selecting randomly one of the clients in the child chromosome and allocating to another place which picked at random and while a crossover fraction considered 0 for this problem then all children are mutation children.

| | | | |
|---|---|---|---|
| *O1* | *C8* | $\longrightarrow$ | *C6* |
| *O2* | *C7* | $\longrightarrow$ | *C8* |

**Replacement population method**

The newly generated child solutions are put back into the original population to replace the less fit members. The average fitness of the population increases as child solutions with better finesses replace the less fit solutions, so it means we used incremental replacement for this problem.

**Population size**

The performance of GA is influenced by the population size. Small populations run the risk of seriously under-covering the solution space, while large populations are computationally intensive [Jaramillo et al, 2002]. we chose a population size equal to n which is equal to the number of clients multiple related depots for this problem.

$$\text{Population size} = \text{Number of clients} * 2 = 6$$

The results of order scheduling using the proposed Genetic Algorithm approach are presented in Table 5.14. It can be seen that the objective function value has improved with respect to the initial solution.

| **Depots** | **Initial solution (TS)** | **Distance** | **Total Distance** | **Final Solution (GA)** | **Distance** | **Total Distance** |
|---|---|---|---|---|---|---|
| D1 | D1 → C6C7C8 → D1 | 27.3 | 121.84 | S1 → D1C7C6C8D1 | 16.32 | 91.88 |
| D2 | D2 → 10C11C9 → D2 | 24.1 | | S1 →D210C9C11D2 | 9.6 | |
| D3 | D3 → C15,C16,C17 → D3 | 11.3 | | S1 →D3C16C15C17D3 | 8.5 | |
| D4 | D4 → C2,C14,C19 → D4 | 22.15 | | S1 → D4C2C19C14D4 | 22.28 | |
| D5 | D5 → C20,C5,C21 →D5 | 12.46 | | S1 → D5C5C21C20 D5 | 12.26 | |
| D6 | D6 → C13,C3,C4 → D6 | 12.83 | | S1 → D6C3C13C4D6 | 11.9 | |
| D7 | D7 → C1,C12,C18 → D7 | 11.7 | | S1 → D7C18C1C12 D7 | 11.02 | |

**Table 5.14: Scheduling results for 21- Customer problem**

To calculate the number of vehicles required to deliver the orders of depot 1, we will need the order quantity requested by the clients. Using the Table 5.13 data, the total order quantity requested by clients of depot 1 = 13200. Using the truck information presented in Table 5.6, we find that two solutions are possible to meet this demand.

Solution 1 = 2 Big Truck + 1 Medium Truck =2 * 5500 = 11000 + 1* 3000 = 14000 >13200, hence sufficient to meet the demand.

Solution 2 = 2Big Truck + 3 small truck = 2*5500+ 3*1000 = 14000 > 13200.

To make the final selection, we will compare the weighted scores for the two solutions as shown in Table 5.15. Since the score of Solution 1 is lesser than Solution 2, therefore Solution 1 is finally selected for vehicle allocation.

| | **Weight** | **Solution 1 (2B , I M)** | **Solution2 (2B,3S)** |
|---|---|---|---|
| **Cost** | 70% | 1700 | 2250 |
| **Emission** | 20% | 155 | 165 |
| **Noise** | 10% | 90 | 100 |
| **Weight** | 100% | 1230 | 1618 |

**Table 5.15: Solution weight scoring for the 21 customer problem**

To generate the vehicle routes, we will use the modified Dijkstra's algorithm. The results of vehicle routing for the customers of the 7 depots are presented in Table 5.16. It can be seen that the final solution has improved for the objective function value with respect to the initial solution.

| Depots | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| D1 | S1 → D1C7C6C8D1 | 16.32 | 91.88 | R1 → C6C7C8 | 14.27 | 78.81 |
| D2 | S1 →D210C9C11D2 | 9.6 | | R1→ C10C9C11 | 9.6 | |
| D3 | S1 →D3 C16C15C17D3 | 8.5 | | R1 → C15C16C17 | 8.5 | |
| D4 | S1 → D4 C2C19C14D4 | 22.28 | | R1 → C14C19C2 | 14.78 | |
| D5 | S1 → D5C5C21C20 D5 | 12.26 | | R1→ C21C5C20 | 12.26 | |
| D6 | S1 → D6 C3C13C4D6 | 11.9 | | R1 → C13C3C4 | 10.9 | |
| D7 | S1 → D7 C18C1C12D7 | 11.02 | | R1 → C18C1C12 | 6.5 | |

**Table 5.16: Routing results for the 21 customer problem**

### 5.2.2. Fifty Customers, Five Depots problem

Table 5.17 presents the weighted travel time information for the 5 depots and 50 customers problem.

| | D1 | D2 | D3 | D4 | D5 |
|---|---|---|---|---|---|
| C1 | 2.9 | 3.2 | 3.5 | 3.14 | 3.15 |
| C2 | 3.9 | 4 | 4.3 | 3.62 | 3.6 |
| C3 | 3.5 | 3.6 | 3.5 | 3.14 | 3.12 |
| C4 | 3.5 | 3.6 | 3.6 | 3.19 | 3.17 |
| C5 | 3.3 | 3.4 | 3 | 2.99 | 3.07 |
| C6 | 3.3 | 3.4 | 3.1 | 3.04 | 3.13 |
| C7 | 3.1 | 3.3 | 3.8 | 3.31 | 3.28 |
| C8 | 2.5 | 2.9 | 3 | 2.83 | 3 |
| C9 | 3.2 | 3.3 | 3 | 2.88 | 2.86 |
| C10 | 4 | 4.1 | 4.6 | 3.76 | 3.74 |
| C11 | 3.1 | 3.3 | 3.4 | 3.1 | 3.28 |
| C12 | 3.1 | 3.4 | 4 | 3.38 | 3.24 |
| C13 | 2.8 | 3 | 3.2 | 2.95 | 3.04 |
| C14 | 3 | 3.2 | 3.6 | 3.18 | 3.03 |

| | | | | | |
|---|---|---|---|---|---|
| **C15** | 3.1 | 3.2 | 2.6 | 2.74 | 2.82 |
| **C16** | 3.2 | 3.3 | 2.8 | 2.88 | 2.97 |
| **C17** | 2.7 | 3 | 3.1 | 2.92 | 3.05 |
| **C18** | 3.5 | 3.14 | 3.15 | 3 | 2.1 |
| **C19** | 4.3 | 3.62 | 3.6 | 4.1 | 5.8 |
| **C20** | 3.5 | 3.14 | 3.12 | 3.6 | 4.8 |
| **C21** | 3.6 | 3.19 | 3.17 | 3.6 | 4.9 |
| **C22** | 3 | 2.99 | 3.07 | 3.4 | 4.6 |
| **C23** | 3.1 | 3.04 | 3.13 | 3.5 | 4.7 |
| **C24** | 3.8 | 3.31 | 3.28 | 3.2 | 1.8 |
| **C25** | 3 | 2.83 | 3 | 2.7 | 3 |
| **C26** | 3 | 2.88 | 2.86 | 3.3 | 4.1 |
| **C27** | 4.6 | 3.76 | 3.74 | 4.2 | 6.1 |
| **C28** | 3.4 | 3.1 | 3.28 | 3.3 | 4.4 |
| **C29** | 4 | 3.38 | 3.24 | 3.2 | 2 |
| **C30** | 3.2 | 2.95 | 3.04 | 2.8 | 2.5 |
| **C31** | 3.6 | 3.18 | 3.03 | 3 | 2.3 |
| **C32** | 2.6 | 2.74 | 2.82 | 3.2 | 4.1 |
| **C33** | 3.5 | 3.14 | 3.15 | 3 | 2.1 |
| **C34** | 4.3 | 3.62 | 3.6 | 4.1 | 5.8 |
| **C35** | 3.5 | 3.14 | 3.12 | 3.6 | 4.8 |
| **C36** | 3.6 | 3.19 | 3.17 | 3.6 | 4.9 |
| **C37** | 3 | 2.99 | 3.07 | 3.4 | 4.6 |
| **C38** | 3.1 | 3.04 | 3.13 | 3.5 | 4.7 |
| **C39** | 3.8 | 3.31 | 3.28 | 3.2 | 1.8 |
| **C40** | 3 | 2.83 | 3 | 2.7 | 3 |
| **C41** | 3 | 2.88 | 2.86 | 3.3 | 4.1 |
| **C42** | 4.6 | 3.76 | 3.74 | 4.2 | 6.1 |
| **C43** | 3.4 | 3.1 | 3.28 | 3.3 | 4.4 |
| **C44** | 4 | 3.38 | 3.24 | 3.2 | 2 |
| **C45** | 3.2 | 2.95 | 3.04 | 2.8 | 2.5 |
| **C46** | 3.6 | 3.18 | 3.03 | 3 | 2.3 |
| **C47** | 2.6 | 2.74 | 2.82 | 3.2 | 4.1 |
| **C48** | 2.8 | 2.88 | 2.97 | 3.3 | 4.4 |
| **C49** | 3.1 | 2.92 | 3.05 | 2.8 | 2.7 |
| **C50** | 2.4 | 2.47 | 2.65 | 2.9 | 3.5 |
| **C51** | 3.1 | 3.4 | 4 | 3.38 | 3.24 |

**Table 5.17: Clients- Depot info for the 50 customer problem**

The allocation results are presented in Table 5.18. The initial solution obtained from NN approach has an objective function of 6583 which has reduced to 6166 after applying Tabu search.

| Depots | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| D1 | C3C5C23C13C4C6 C19C27C38C42 | 1276 | 6583 | C41C18C32C13C4C6 C19C27C38C42 | 1165 | 6166 |
| D2 | C28C33C14C43C41 C18C32C44C20C40 | 1365 | | C33C14C43C3C5C23 C28C44C20C40 | 1276 | |
| D3 | C45C22C1C7C35C 39C37C46C50C36 | 1287 | | C22C1C15C34C29C2 4C7C35C39C45 | 1196 | |
| D4 | C17C31C2C30C16 C11C21C8C9C2 | 1398 | | C50C36C2C30C16C1 1C21C8C9C2 | 1309 | |
| D5 | C15C34C29C24C49 C12C48C26C10C47 | 1257 | | C17C31C37C46C49C 12C48C26C10C47 | 1222 | |

**Table 5.18: Allocation results for 50- Customer problem**

The order details of customers are shown in Table 5.19.

| Depot | Clients | Total Order Quantity |
|---|---|---|
| D1 | C3C5C23C13C4C6C19C27C38C42 | 8500 |
| D2 | C28C33C14C43C41C18C32C44C20C40 | 6000 |
| D3 | C45C22C1C7C35C39C37C46C50C36 | 8500 |
| D4 | C17C31C2C30C16C11C21C8C9C2 | 8500 |
| D5 | C15C34C29C24C49C12C48C26C10C47 | 8500 |

**Table 5.19: Customer Order quantities for the 50 customer problem**

The other order scheduling related information for the 50 customer problem can be found in Table 5.20.

| Criteria | Loading Time | Transit Time | Historical Delay Time(city) | Packing Time | Access Time to Facility | Unloading Time | Weighted Client Score |
|---|---|---|---|---|---|---|---|
| Weight | 10% | 30% | 20% | 15% | 10% | 15% | 100% |
| C1 | 0 | 231.6 | 10 | 0 | 0 | 321.6 | 11972 |
| C2 | 22.04 | 133 | 30 | 0 | 0 | 223 | 8155.4 |
| C3 | 0 | 1087 | 10 | 0 | 0 | 1177 | 50465 |
| C4 | 0.28 | 1181 | 10 | 0 | 0 | 1271 | 54697.8 |
| C5 | 0 | 15.13 | 10 | 0 | 0 | 105.13 | 2230.85 |
| C6 | 0 | 736 | 20 | 0 | 0 | 826 | 34870 |
| C7 | 0 | 1254 | 10 | 0 | 0 | 1014 | 53030 |
| C8 | 0 | 3210 | 20 | 0 | 0 | 1110 | 113350 |
| C9 | 0 | 2930 | 10 | 0 | 0 | 1301 | 107615 |
| C10 | 0 | 3120 | 40 | 0 | 0 | 1488 | 116720 |
| C11 | 0 | 3027 | 30 | 0 | 0 | 1676 | 116550 |
| C12 | 0 | 2448 | 10 | 0 | 0 | 1847 | 101345 |
| C13 | 0 | 2734 | 20 | 0 | 0 | 2071 | 113485 |
| C14 | 0 | 2540 | 10 | 0 | 0 | 2355 | 111725 |
| C15 | 0 | 2541 | 10 | 0 | 0 | 2448 | 113150 |
| C16 | 0 | 3200 | 20 | 0 | 0 | 2640 | 136000 |
| C17 | 0 | 1542 | 20 | 0 | 0 | 2734 | 87670 |
| C18 | 0 | 1140 | 10 | 0 | 0 | 3027 | 79805 |
| C19 | 0 | 2651 | 10 | 0 | 0 | 3120 | 126530 |
| C20 | 0 | 10 | 20 | 0 | 0 | 3217 | 48955 |
| C21 | 0 | 2032 | 30 | 0 | 0 | 3211 | 109725 |
| C22 | 0 | 1254 | 40 | 0 | 0 | 1301 | 57935 |
| C23 | 0 | 2541 | 10 | 0 | 0 | 922 | 90260 |
| C24 | 159.02 | 2541 | 20 | 0 | 0 | 826 | 90610.2 |
| C25 | 0 | 2562 | 20 | 0 | 0 | 727 | 88165 |
| C26 | 0 | 2448 | 10 | 0 | 0 | 2640 | 113240 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **C27** | 0 | 2734 | 40 | 0 | 0 | 2166 | 115310 |
| **C28** | 0 | 2540 | 30 | 0 | 0 | 2833 | 119295 |
| **C29** | 0 | 2541 | 10 | 0 | 0 | 2930 | 120380 |
| **C30** | 0 | 3200 | 20 | 0 | 0 | 3212 | 144580 |
| **C31** | 0 | 1542 | 20 | 0 | 0 | 2522 | 84490 |
| **C32** | 0 | 1140 | 10 | 0 | 0 | 2541 | 72515 |
| **C33** | 0 | 2651 | 40 | 0 | 0 | 736 | 91370 |
| **C34** | 0 | 10 | 30 | 0 | 0 | 2444 | 37560 |
| **C35** | 0 | 1205 | 10 | 0 | 0 | 2640 | 75950 |
| **C36** | 0 | 1401 | 20 | 0 | 0 | 2355 | 77755 |
| **C37** | 0 | 1211 | 10 | 0 | 0 | 2445 | 73205 |
| **C38** | 0 | 1393 | 10 | 0 | 0 | 1303 | 61535 |
| **C39** | 0 | 1488 | 20 | 0 | 0 | 1398 | 66010 |
| **C40** | 749.84 | 1776 | 20 | 0 | 0 | 2540 | 99278.4 |
| **C41** | 0 | 1874 | 10 | 0 | 0 | 1020 | 71720 |
| **C42** | 0 | 1972 | 40 | 0 | 0 | 2448 | 96680 |
| **C43** | 0 | 2166 | 30 | 0 | 0 | 2734 | 106590 |
| **C44** | 0 | 2355 | 10 | 0 | 0 | 2540 | 108950 |
| **C45** | 0 | 2445 | 20 | 0 | 0 | 2541 | 111865 |
| **C46** | 0.15 | 3027 | 10 | 0 | 0 | 321.6 | 95835.5 |
| **C47** | 93 | 3120 | 10 | 0 | 0 | 223 | 98075 |
| **C48** | 0 | 3124 | 20 | 0 | 0 | 1177 | 111775 |
| **C49** | 855.95 | 3222 | 20 | 0 | 0 | 1271 | 124685 |
| **C50** | 92.13 | 1776 | 10 | 0 | 0 | 105.13 | 55978.3 |
| **C51** | 0 | 1667 | 10 | 0 | 0 | 826 | 62600 |

**Table 5.20: Order Scheduling Information for 50- Customer problem**

The order scheduling results obtained from Genetic Algorithm is presented in Table 5.21. It can be seen that the objective function value has improved over time.

| Depots | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Total D | Total Distance |
|---|---|---|---|---|---|---|
| D1 | D1C41C18C32C13 C4C6C19C27C38 C42D1 | 1281.5 | 6061.5 | S1 = D1C18C13C6C19C 27C41C32C4C38C4 2D1 | 1065 | 5479 |
| D2 | D2C33C14C43C3 C5C23C28C44C20 C40D2 | 1164 | | S1 = D2C33C14C44C20 C40C43C3C5C23C 28D2 | 1129 | |
| D3 | D3C22C1C15C34 C29C24C7C35C39 C45D3 | 1218 | | S1 = D3C24C7C35C39C 45C22C1C15C34C2 9D3 | 1076 | |
| D4 | D4C50C36C2C30 C16C11C21C8C9 C2D4 | 1075 | | S1 = D4C11C21C8C9C2 C50C36C2C30C16 D4 | 987 | |
| D5 | D5C17C31C37C46 C49C12C48C26C1 0C47D5 | 1323 | | S1 = D5C17C31C26C10 C47C37C46C49C12 C48 D5 | 1222 | |

**Table 5.21: Scheduling results for 50- Customer problem**

Using the vehicle details provided in Table 5.6 and order quantities of Table 5.19, we calculated the possible solutions for each depot and evaluated them using the weighted score method. For depots D1, D3, D5, D6, the order quantity requested is 8500 and the various solution combinations possible for vehicle allocations are 2B.3S, 1B.1 M, and 1B.3S. For depot D2, the order quantity requested is 6000 and the solution combinations possible for vehicle allocations are 2M, 1B.1S, and 1M.3S. The weighted scores for the various possible vehicle allocations are presented in Table 5.22. The solutions finally chosen for each depot are highlighted in yellow.

| D1 | | | | |
|---|---|---|---|---|
| **Criteria** | **Weight** | **Solution 1 (2B.3S)** | **Solution2 (1B,1 M)** | **Solution3 (1B,3S)** |
| **Cost** | 70% | 1550 | 1700 | 1650 |

| | | | | |
|---|---|---|---|---|
| **Emission** | 20% | 85 | 75 | 95 |
| **Noise** | 10% | 65 | 45 | 65 |
| **Weight** | 100% | 1106 | 1209 | 1178 |
| | | **D2** | | |
| **D2** | **Weight** | **Solution 1 (2M)** | **Solution2 (1 B,1S)** | **Solution3 (1M,3S)** |
| **Cost** | 70% | 1000 | 1100 | 1300 |
| **Emission** | 20% | 40 | 45 | 75 |
| **Noise** | 10% | 65 | 30 | 45 |
| **Weight** | 100% | 714 | 785 | 929 |
| | | **D3** | | |
| **D3** | **Weight** | **Solution 1 (2B.3S)** | **Solution2 (1 B,1 M)** | **Solution3 (1B,3S)** |
| **Cost** | 70% | 1550 | 1700 | 1650 |
| **Emission** | 20% | 85 | 75 | 95 |
| **Noise** | 10% | 65 | 45 | 65 |
| **Weight** | 100% | 1106 | 1209 | 1178 |
| | | **D4** | | |
| **D4** | **Weight** | **Solution 1 (2B.3S)** | **Solution2 (1 B,1 M)** | **Solution3 (1B,3S)** |
| **Cost** | 70% | 1550 | 1700 | 1650 |
| **Emission** | 20% | 85 | 75 | 95 |
| **Noise** | 10% | 65 | 45 | 65 |
| **Weight** | 100% | 1106 | 1209 | 1178 |
| | | **D5** | | |
| **Criteria** | **Weight** | **Solution 1 (2B.3S)** | **Solution2 (1 B,1 M)** | **Solution3 (1B,3S)** |
| **Cost** | 70% | 1550 | 1700 | 1650 |
| **Emission** | 20% | 85 | 75 | 95 |
| **Noise** | 10% | 65 | 45 | 65 |
| **Weight** | 100% | 1106 | 1209 | 1178 |

**Table 5.22: Vehicle allocation results for 50- Customer problem**

Now, we generate delivery routes for the allocated vehicles using modified Dijkstra's algorithm. The results are presented in Table 5.24. It can be seen that the objective function value has improved with respect to the initial solution.

| Depot | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| D1 | S1 = D1C18C13C6C19C27 C41C32C4C38C42D1 | 1065 | 5479 | R1 = D1C13C18C6C27C19 C4C41C32C42C38 D1 | 1020 | 5311 |
| D2 | S1 = D2C33C14C44C20C4 0C43C3C5C23C28D2 | 1129 | | R1 = D2C14C33C40C44C20 C5C43C3C28C23D2 | 1102 | |
| D3 | S1 = D3C24C7C35C39C45 C22C1C15C34C29D3 | 1076 | | R1 = D3C7C35C24C39C45 C15C34C22C1C29D3 | 1065 | |
| D4 | S1 = D4C11C21C8C9C2C5 0C36C2C30C16D4 | 987 | | R1 = D4C11C8C21C9C2D4 C36C2 C50C16 C30D4 | 950 | |
| D5 | S1 = D5C17C31C26C10C4 7C37C46C49C12C48 D5 | 1222 | | R1 = D5C47C17C31C26C10 C12C37C49 C46C48 D5 | 1174 | |

**Table 5.23: Routing results for 50- Customer problem**

The computation times and the number of iterations required for the 6-customer, 21-customer and 50-customer problems are presented in Table 5.24.

| Problem Type | Allocation | | Scheduling | | Routing | |
|---|---|---|---|---|---|---|
| | Computation Time | Iteration | Computation Time | Iteration | Computation Time | Iteration |
| 6-customer, 2 depots | 6 | 1044 | 4 | 18 | 4 | 18 |
| 21-customer, 7 depots | 30 | 1339 | 14 | 63 | 14 | 63 |
| 50-customer, 5 depots | 141 | 256272 | 33 | 3060 | 64 | 591 |

**Table 5.24: Computation times and iterations for Model Verification**

It can be seen from the results of Table 5.24 that as the problem size increases, the computation time and the number of iterations increases. Besides, the objective function values decreases as indicated in the allocation, scheduling and routing results for 6-customer, 21-customer, and 50 customer problem instances. This verifies the results of our proposed approaches for these problems.

## 5.3 Model Validation

To perform the validation of our model results, we tested the proposed approaches on the Solomon's benchmark problems for 50 customers and 3 depots. The problem details can be found at the website.

http://web.cba.neu.edu/~msolomon/problems.htm

There are 6 six sets of problems (R1,R2,C1,C2,RC1,RC2). The geographical data are randomly generated in problem sets R1 and R2, clustered in problem sets C1 and C2, and a mix of random and clustered structures in problem sets by RC1 and RC2. Problem sets R1, C1 and RC1 have a short scheduling horizon and allow only a few customers per route (approximately 5 to 10). In contrast, the sets R2, C2 and RC2 have a long scheduling horizon permitting many customers (more than 30) to be serviced by the same vehicle. For each of these problem sets, information s available on geographical data; the number of customers serviced by a vehicle; percent of time-constrained customers; and tightness and positioning of the time windows.

Table 5.25 presents the allocation results for the problem R1. It can be seen that objective function value has improved for the three problem instances for the R1 problem category, thereby showing the effectiveness of the proposed NN-TS approach in addressing balanced customer allocation problems on logistics networks.

| | **Initial solution (NN)** | **Distance** | **Total Distance** | **Final Solution (TS)** | **Distance** | **Total Distance** |
|---|---|---|---|---|---|---|
| R101 | D1 → C3C44C4C6C12C34C3C24C25C45C5C465C14C42C43C13C15 | 1200 | 3900 | D1 → C50C4C6C20C27C3C24C25C45C3C5C46C14C42C16C13C38 | 1100 | 3450 |
| | D2 → C7C21C22C33C17C31C41C32C47C18C27C28C23C40C49C8C48 | 1250 | | D2 → C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48 | 1050 | |
| | D3→ C1C9C37C20C10C2C19C50C26C29C30C36C11C38C16C39 | 1450 | | D3→ C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15 | 1300 | |
| R102 | D1 → C24C25C45C5C465C14C42C3C44C4C6C12C34C3C43C13C15 | 1430 | 4625 | D1 → C20C16C27C3C38C24C4C6C25C45C3C5C46C14C50C42C13 | 1345 | 4484 |
| | D2 → C31C41C32C47C18C27C7C21C22C33C17C28C23C40C49C8C48 | 1565 | | D2 → C34C40C17C31C49C12C32C47C18C7C21C19C28C33C23C8C48 | 1563 | |
| | D3→ C10C2C19C50C26C29C30C1C37C20C36C11C9C38C16C39 | 1630 | | D3→ C26C29C1C43C30C15C39C9C37C41C22C44C36C10C2C11 | 1576 | |
| R103 | D1 → C3C44C4C6C12C34C3C24C25C45C5C465C14C42C43C13C15 | 1535 | 4310 | D1 → C50C4C6C20C27C3C24C25C45C3C5C46C14C42C16C13C38 | 1521 | 4122 |
| | D2 → C7C21C22C33C17C31C41C32C47C18C27C28C23C40C49C8C48 | 1232 | | D2 → C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48 | 1114 | |
| | D3→ C1C9C37C20C10C2C19C50C26C29C30C36C11C38C16C39 | 1543 | | D3→ C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15 | 1487 | |

**Table 5.25: Allocation Results for R1**

Table 5.26 presents the results of order scheduling for the R1 problem. It can be seen in Table 5.26 that objective function value has improved for the three problem instances, thereby showing the effectiveness of the proposed GA approach in addressing order scheduling problems for customers.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| R101 | D1C50C4C6C20C27C3C24C25C45C3C5C46C14C42C16C13C38D1 | 1178 | 3668 | S1 → D1C6C20C27C3C24C25C45C3C38C50C4C5C46C14C42C16C13D1 | 1165 | 3648 |
| | D2C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48D2 | 1167 | | S1 → D2C19C33C17C31C12C32C47C18C40C7C21C34C28C23C49C8C48D2 | 1134 | |
| | D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3 | 1323 | | S1 → D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3 | 1349 | |
| R102 | D1C20C16C27C3C38C24C4C6C25C45C3C5C46C14C50C42C13D1 | 1387 | 4671 | S1 → D1C38C20C27C3C24C16C4C13C6C25C3C5C46C45C14C42C50D1 | 1298 | 4578 |
| | D2C34C40C17C31C49C12C32C47C18C7C21C19C28C33C23C8C48D2 | 1498 | | S1 → D2C23C34C31C18C49C33C48C12C40C17C32C47C7C21C19C28C8D2 | 1519 | |
| | D3C26C29C1C43C30C15C39C9C37C41C22C44C36C10C2C11D3 | 1786 | | S1 → D3C22C26C30C15C39C9C37C11C44C10C36C1C29C41C43C2D3 | 1561 | |
| R103 | D1 C50C4C6C20C27C3C24C25C45C3C5C46C14C42C16C13C38D1 | 1578 | 4157 | S1 → D1C4C6C27C24C25C45C3C5C38C46C20C14C50C42C3C16C13D1 | 1456 | 4149 |
| | D2C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48D2 | 1234 | | S1 → D2C40C31C21C17C19C32C7C33C18C12C47C34C28C23C49C8C48D2 | 1136 | |
| | D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3 | 1345 | | S1 → D3C36C11C1C30C10C9C22C26C43C39C37C41C2C44C29C15D3 | 1557 | |

**Table 5.26: Scheduling Results for R1**

Table 5.27 presents the results of vehicle routing for the R1 problem. It can be seen in Table 5.27 that objective function value has improved for the three problem instances, thereby showing the effectiveness of the proposed Modified Dijkstra's approach in addressing routing problems.

| | | Initial solution<br>(GA) | Distance | Total Distance | Final Solution<br>(DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|---|
| **R101** | **D1** | **S1 → D1C6C20C27C3C24C25C45C3C38C50C4C5C46C14C42C16C13D1** | 1165 | 3648 | **R1 → D1C27C6C3C45C24C20C25C3C38C42C16C50C5C46C14C4C13D1** | **1245** | **3644** |
| | **D2** | **S1 → D2C19C33C17C31C12C32C47C18C40C7C21C34C28C23C49C8C48D2** | 1134 | | **R1 → D2C17C19C33C32C31C12C18C47C7C21C40C28C23C49C34C8C48D2** | **1034** | |
| | **D3** | **S1 → D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3** | 1349 | | **R1 → D3C10C43C9C37C41C39C1C2C36C22C44C29C30C11C26C15D3** | **1365** | |
| **R102** | **D1** | **S1 → D1C38C20C27C3C24C16C4C13C6C25C3C5C46C45C14C42C50D1** | 1298 | 4578 | **R1 → D1C3C6C24C38C20C27C4C13C16C45C25C5C50C46C14C42C3D1** | **1245** | **4312** |
| | **D2** | **S1 → D2C23C34C31C18C49C33C48C12C40C17C32C47C7C21C19C28C8D2** | 1519 | | **R1 →D2C23C48C49C34C31C18C12C33C17C40C32C47C19C7C21C28C8D2** | **1469** | |
| | **D3** | **S1 → D3C22C26C30C15C39C9C37C11D3**<br>**S2 →D3C44C10C36C1C29C41C43C2D3** | 1561 | | **R1 →D3C2C2C30C37C15C39C26C9C11C1C43C29C44C10C36C41C2D3** | **1598** | |
| **R103** | **D1** | **S1 → D1C4C6C27C24C25C45C3C5C38C46C20C14C50C42C3C16C13D1** | 1456 | 4149 | **R1 →D1 C45C4C27C24C6C25C3C5C38C14C46C50C20C3C16C42C13D1** | **1431** | **4205** |
| | **D2** | **S1 → D2C40C31C21C17C19C32C7C33C18C12C47C34C28C23C49C8C48D2** | 1136 | | **R1 → D2C17C40C31C33C19C21C32C7C18C12C49C23C48C47C34C8C28D2** | **1287** | |
| | **D3** | **S1 → D3C36C11C1C30C10C9C22C26C43C39C37C41C2C44C29C15D3** | 1557 | | **R1 →D3C10C9C22C26C36C11C1C30C44C29C15C43C39C37C41C2D3** | **1487** | |

**Table 5.27: Routing results for R1**

Table 5.28 presents the allocation results for the problem C1. It can be seen that objective function value has improved for the three problem instances for the C1 problem

| | **Initial solution (NN)** | **Distance** | **Total Distance** | **Final Solution (TS)** | **Distance** | **Total Distance** |
|---|---|---|---|---|---|---|
| C101 | D1 → C25C45C5C465C14C42C43C3C44C4C6C12C34C3C24 | 1222 | 3916 | D1 → C27C3C24C25C45C50C4C6C20C3C5C46C14C42C16C13C | 1134 | 3676 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | C13C15 | | | 38 | | |
| | D2 → C31C41C32C47C7C21C22C33C17C18C27C28C23C40C49C8C48 | 1240 | | D2 → C19C33C17C31C12C40C7C21C32C47C18C34C28C23C49C8C48 | 1178 | |
| | D3→ C19C50C26C29C30C1C9C37C20C10C2C36C11C38C16C39 | 1454 | | D3→ C10C2C22C44C26C43C39C1C9C37C41C29C30C36C11C15 | 1364 | |
| C102 | D1 → C24C25C45C4C6C12C34C3C43C5C465C14C42C3C44C13C15 | 1419 | 4651 | D1 → C6C25C45C3C20C16C27C3C38C24C4C5C46C14C50C42C13 | 1349 | 4323 |
| | D2 → C22C33C17C28C31C41C32C47C18C27C7C21C23C40C49C8C48 | 1576 | | D2 → C31C49C12C32C47C18C34C40C17C7C21C19C28C33C23C8C48 | 1466 | |
| | D3→ C26C2C19C50C36C29C30C1C37C20C10C11C9C38C16C39 | 1656 | | D3→ C39C9C37C41C22C26C29C1C43C30C15C44C36C10C2C11 | 1556 | |
| C103 | D1 → C34C3C24C25C45C5C3C44C4C6C12C465C14C42C43C13C15 | 1520 | 4321 | D1 → C45C3C5C46C50C4C6C20C27C3C24C25C14C42C16C13C38 | 1453 | 4109 |
| | D2 → C7C21C22C33C17C31C41C32C47C18C27C28C23C40C49C8C48 | 1247 | | D2 → C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48 | 1134 | |
| | D3→ C1C30C36C11C38C9C37C20C10C2C19C50C26C29C16C39 | 1555 | | D3→ C41C10C2C22C43C39C1C9C37C44C26C29C30C36C11C15 | 1432 | |

**Table 5.28: Allocation Results for C1**

Table 5.29 presents the results of customer order scheduling for the C1 problem. It can be seen in Table 5.29 that objective function value has improved for the three problem instances.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| C101 | D1C27C3C24C25C45C50C4C6C20C3C5C46C14C42C16C13C38D1 | 1178 | 3751 | S1 → D1C3C24C25C45C6C20C27C3C38C46C14C42C50C4C5C16C13D1 | 1179 | 3757 |
| | D2C19C33C17C31C12C40C7C21C32 | 1236 | | S1 → | 1259 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | C47C18C34C28C23C49C8C48D2 | | | D2C33C17C31C19C12C32C47C18C28C23C49C40C7C21C34C8C48D2 | | |
| | D3 C10C2C22C44C26C43C39C1C9C37C41C29C30C36C11C15D3 | 1337 | | S1 → D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3 | 1319 | |
| C102 | D1C6C25C45C3C20C16C27C3C38C24C4C5C46C14C50C42C13D1 | 1351 | 4365 | S1 → D1C27C3C24C38C20C16C4C13C6C46C45C14C25C3C5C42C50D1 | 1410 | 4456 |
| | D2C31C49C12C32C47C18C34C40C17C7C21C19C28C33C23C8C48D2 | 1476 | | S1 → D2C31C18C49C23C34C33C48C12C32C47C7C21C40C17C19C28C8D2 | 1457 | |
| | D3C39C9C37C41C22C26C29C1C43C30C15C44C36C10C2C11D3 | 1576 | | S1 → D3C15C39C9C22C26C30C37C11C36C1C29C44C10C41C43C2D3 | 1589 | |
| C103 | D1C45C3C5C46C50C4C6C20C27C3C24C25C14C42C16C13C38D1 | 1558 | 4329 | S1 → D1C24C25C45C4C6C27C3C5C38C14C50C42C46C20C3C16C13D1 | 1445 | 4266 |
| | D2C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48D2 | 1239 | | S1 → D2C21C17C19C40C31C32C7C33C18C34C28C23C49C12C47C8C48D3 | 1345 | |
| | D3C41C10C2C22C43C39C1C9C37C44C26C29C30C36C11C15D3 | 1542 | | S1 → D3C30C10C9C36C11C1C22C26C37C41C2C43C39C44C29C15D3 | 1476 | |

**Table 5.29: Scheduling Results for C1**

Table 5.30 presents the results of vehicle routing for the C1 problem. It can be seen in Table 5.30 that objective function value has improved for the three problem instances.

| | | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|---|
| C101 | D1 | S1 → D1C3C24C25C45C6C20C27C3C38C46C14C42C50C4C5C16C13D1 | 1179 | 3757 | R1 → D1C3C45C24C20C27C6C25C3C381C50C5C46C42C16C14C4C13D1 | 1189 | 3735 |
| | D2 | S1 → D2C33C17C31C19C12C32C47C18C28C23C49C40C7C21C34C8C48D2 | 1259 | | R1 → D2C32C31C12C17C19C33C18C47C28C23C49C7C21C40C34C8C48D2 | 1235 | |
| | D3 | S1 → D3C43C39C1C9C37C41C10C2C22C44C26C29C30C36C11C15D3 | 1319 | | R1 → D3C9C37C41C43C39C1C10C2C30C11C36C22C44C29C26C15D3 | 1311 | |
| C102 | D1 | S1 → D1C27C3C24C38C20C16C4C13C6C46C45C14C25C3C5C42C50D1 | 1410 | 4456 | R1 → D1C38C20C27C3C6C24C4C13C16C5C50C46C45C25C14C42C3D1 | 1248 | 4159 |
| | D2 | S1 → D2C31C18C49C23C34C33C48C12C32C47C7C21C40C17C19C28C8D2 | 1457 | | R1 → D2C49C34C31C23C48C18C12C33C47C19C7C17C40C32C21C28C8D2 | 1364 | |
| | D3 | S1 → D3C15C39C9C22C26C30C37C11C36C1C29C44C10C41C43C2D3 | 1589 | | R1 → D3C2C39C26C9C11C22C30C37C15C1C43C29C41C2C44C10C36D3 | 1547 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| C103 | D1 | S1 → D1C24C25C45C4C6C27C3C5C38C14C50C42C46C20C3C16C13D1 | 1445 | 4266 | R1 → D1C6C25C3C45C4C27C24C5C38C50C20C3C16C14C46C42C13D1 | 1378 | 4188 |
| | D2 | S1 → D2C21C17C19C40C31C32C7C33C18C34C28C23C49C12C47C8C48D3 | 1345 | | R1 → D2C33C19C21C17C40C31C32C7C18C48C47C12C49C23C34C8C28D2 | 1267 | |
| | D3 | S1 → D3C30C10C9C36C11C1C22C26C37C41C2C43C39C44C29C15D3 | 1476 | | R1 → D3C36C11C1C30C10C9C22C26C44C29C15C37C41C2C43C39D3 | 1543 | |

**Table 5.30: Routing results for C1**

Table 5.31 presents the results of customer allocation for the RC1 problem. It can be seen in Table 5.31 that objective function value has improved for the three problem instances.

| | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| RC101 | D1 → C43C3C44C4C25C45C5C465C14C42C6C12C34C3C24 C13C15 | 1342 | 4236 | D1 → C25C45C50C4C6C20C3C27C3C24C5C46C14C42C16C13C38 | 1187 | 3987 |
| | D2 → C7C21C22C33C17C31C41C32C47C18C27C28C23C40C49C8C48 | 1232 | | D2 → C17C31C12C40C19C33C7C21C32C47C18C34C28C23C49C8C48 | 1221 | |
| | D3→ C29C30C1C9C37C19C50C26C20C10C2C36C11C38C16C39 | 1345 | | D3→ C44C26C43C39C1C10C2C22C9C37C41C29C30C36C11C15 | 1321 | |
| RC102 | D1 → C12C34C3C43C5C24C25C45C4C6C465C14C42C3C44 C13C15 | 1476 | 4521 | D1 → C6C25C24C4C5C46C14C50C42C13C45C3C20C16C27C3C38 | 1342 | 4087 |
| | D2 → C28C31C41C32C22C33C17C47C18C27C7C21C23C40C49C8C48 | 1543 | | D2 → C49C12C32C47C18C31C34C40C17C7C21C19C28C33C23C8C48 | 1496 | |
| | D3→ C50C36C29C30C1C26C2C19C37C20C10C11C9C38C16C39 | 1645 | | D3→ C41C22C26C29C1C39C9C37C43C30C15C44C36C10C2C11 | 1596 | |
| RC103 | D1 → C5C3C44C4C6C12C46C34C3C24C25C455C14C42C43 C13C15 | 1542 | 4529 | D1 → C50C4C6C20C27C45C3C5C46C3C24C25C14C42C16C13C38 | 1492 | 4321 |
| | D2 → C17C31C41C32C47C7C21C22C33C18C27C28C23C40C49C8C48 | 1342 | | D2 → C33C17C31C12C40C7C21C19C32C47C18C34C28C23C49C8C48 | 1323 | |
| | D3→ C38C9C37C20C10C2C1C30C36C11C19C50C26C29C16C39 | 1454 | | D3→ C43C39C1C9C37C44C41C10C2C22C26C29C30C36C11C15 | 1544 | |

**Table 5.31: Allocation Results for RC1**

Table 5.32 presents the results of customer order scheduling for the RC1 problem. It can be seen in Table 5.32 that objective function value has improved for the three problem instances.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| RC101 | D1C25C45C50C4C6C20C3C27C3C24C5C46C14C42C16C13C38D1 | 1197 | 3850 | S1 → D1C25C45C6C20C27C3C24C3C38C4C5C16C46C14C42C50C13D1 | 1238 | 3721 |
| | D2C17C31C12C40C19C33C7C21C32C47C18C34C28C23C49C8C48D2 | 1319 | | S1 → D2C31C19C12C33C17C32C47C18C49C40C7C21C28C23C34C8C48D2 | 1196 | |
| | D3C44C26C43C39C1C10C2C22C9C37C41C29C30C36C11C15D3 | 1334 | | S1 → D3C9C37C41C43C39C1C10C2C26C29C30C22C44C36C11C15D3 | 1287 | |
| RC102 | D1C6C25C24C4C5C46C14C50C42C13C45C3C20C16C27C3C38D1 | 1382 | 4383 | S1 → D1C38C20C16C27C3C24C4C13C6C14C25C3C5C46C45C42C50D1 | 1394 | 4403 |
| | D2C49C12C32C47C18C31C34C40C17C7C21C19C28C33C23C8C48D2 | 1434 | | S1 → D2C31C18C49C23C34C33C48C12C32C47C7C21C40C17C19C28C8D2 | 1476 | |
| | D3C41C22C26C29C1C39C9C37C43C30C15C44C36C10C2C11D3 | 1567 | | S1 → D3C15C39C9C22C26C30C37C11C36C1C29C44C10C41C43C2D3 | 1533 | |
| RC103 | D1C50C4C6C20C27C45C3C5C46C3C24C25C14C42C16C13C38D1 | 1478 | 4385 | S1 → D1C25C45C4C6C24C27C3C5C38C20C3C16C14C50C42C46C13D1 | 1476 | 4536 |
| | D2C33C17C31C12C40C7C21C19C32C47C18C34C28C23C49C8C48D2 | 1345 | | S1 → D2C19C40C31C21C17C32C7C33CC23C49C12C34C28C47C8C48D2 | 1467 | |
| | D3C43C39C1C9C37C44C41C10C2C22C26C29C30C36C11C15D3 | 1562 | | S1 → D3C9C36C11C30C10C1C22C26C2C43C39C37C41C44C29C15D3 | 1593 | |

**Table 5.32: Scheduling Results for RC1**

Table 5.33 presents the results of vehicle routing for the RC1 problem. It can be seen in Table 5.33 that objective function value has improved for the three problem instances.

| | | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|---|
| RC101 | D1 | S1 → D1C25C45C6C20C27C3C24C3C38C4C5C16C46C14C42C50C13D1 | 1238 | 3721 | R1 → D1C27C6C25C3C45C24C20C3C38C46C42C16C50C5C14C4C13D1 | 1184 | 3374 |
| | D2 | S1 → D2C31C19C12C33C17C32C47C18C49C40C7C21C28C23C34C8C48D2 | 1196 | | R1 → D2C12C17C19C32C31C33C18C47C49C7C21C28C23C40C34C8C48D2 | 1045 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | D3 | S1 → D3C9C37C41C43C39C1C10C2C26C29C30C22C44C36C11C15D3 | 1287 | | R1 → D3C41C43C39C9C37C1C10C2C36C22C44C30C11C29C26C15D3 | 1145 | |
| RC102 | D1 | S1 → D1C38C20C16C27C3C24C4C13C6C14C25C3C5C46C45C42C50D1 | 1394 | 4403 | R1 → C27C3C6C38C20C24C4C13C16C46C45C25C5C50C14C42C3 | 1386 | 4185 |
| | D2 | S1 → D2C31C18C49C23C34C33C48C12C32C47C7C21C40C17C19C28C8D2 | 1476 | | R1 → C31C23C48C49C34C18C12C33C7C17C40C47C19C32C21C28C8 | 1376 | |
| | D3 | S1 → D3C15C39C9C22C26C30C37C11 C36C1C29C44C10C41C43C2D3 | 1533 | | R1 → C9C11C22C2C39C26C30C37C15C29C41C2C1C43C44C10C36 | 1423 | |
| RC103 | D1 | S1 → D1C25C45C4C6C24C27C3C5C38C20C3C16C14C50C42C46C13D1 | 1476 | 4536 | R1 → C3C45C4C27C24C6C25C5C38C20C3C16C50C14C46C42C13 | 1433 | 4351 |
| | D2 | S1 → D2C19C40C31C21C17C32C7C33CC23C49C12C34C28C47C8C48D2 | 1467 | | R1 → C21C17C40C33C19C31C32C7C18C12C49C23C48C47C34C8C28 | 1387 | |
| | D3 | S1 → D3C9C36C11C30C10C1C22C26C2C43C39C37C41C44C29C15D3 | 1593 | | R1 → C30C10C36C11C1C9C22C26C15C37C41C44C29C2C43C39 | 1531 | |

**Table 5.33: Routing results for RC1**

Table 5.34 presents the results of customer allocation for the R2 problem. It can be seen in Table 5.34 that objective function value has improved for the three problem instances.

| | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| R201 | D1 → C12C34C3C24C25C3C44C4C6C45C5C465C14C42C43 C13C15 | 1232 | 4566 | D1 → C20C27C3C14C42C50C4C6C24C25C45C3C5C46C16C13C38 | 1187 | 4167 |
| | D2 → C31C41C32C47C18C7C21C22C33C17C27C28C23C40C49C8C48 | 1342 | | D2 → C47C40C7C21C19C12C32C33C17C31C18C34C28C23C49C8C48 | 1256 | |
| | D3→ C2C19C50C26C29C1C9C37C20C10C30C36C11C38C16C39 | 1455 | | D3→ C10C2C43C39C1C9C22C44C37C41C26C29C30C36C11C15 | 1411 | |
| R202 | D1 → C3C44C4C6C12C24C25C45C5C465C14C42C34C3C43C13C15 | 1346 | 4451 | D1 → C6C20C16C27C3C38C24C4C25C45C3C5C46C14C50C42C13 | 1332 | 4323 |
| | D2 → C47C18C27C7C21C31C41C32C22C33C17C28C23C40C49C8C48 | 1253 | | D2 → C17C32C47C31C49C12C34C40C18C7C21C19C28C33C23C8C48 | 1199 | |
| | D3→ | 1875 | | D3→ | 1811 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | C20C36C11C10C2C19C50C26C29C30C1C37 C9C38C16C39 | | | C39C26C29C1C9C37C41C43C30C15C22 C44C36C10C2C11 | | |
| R203 | D1 → C4C6C12C34C3C24C25C3C44C45C5C465C1 4C42C43 C13C15 | 1452 | 4769 | D1 → C27C45C3C5C46C3C24C25C50C4C6C20 C14C42C16C13C38 | 1423 | 4567 |
| | D2 → C32C47C18C27C28C7C21C22C33C17C31C4 1C23C40C49C8C48 | 1342 | | D2 → C40C7C21C12C32C19C33C17C31C47C1 8C34C28C23C49C8C48 | 1321 | |
| | D3→ C1C9C37C20C10C2C19C50C26C29C30C36C 11C38C16C39 | 1574 | | D3→ C39C1C9C2C22C44C37C41C10C43C26C 29C30C36C11C15 | 1529 | |

**Table 5.34: Allocation Results for R2**

Table 5.35 presents the results of customer order scheduling for the R2 problem. It can be seen in Table 5.35 that objective function value has improved for the three problem instances.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distanc e |
|---|---|---|---|---|---|---|
| R201 | D1C20C27C3C14C42C50C4C6C24 C25C45C3C5C46C16C13C38D1 | 1267 | 3980 | S1 → D1C6C20C27C24C25C45C3C3C38C13 C50C4C42C16C5C46C14D1 | 1237 | 3956 |
| | D2C47C40C7C21C19C12C32C33C 17C31C18C34C28C23C49C8C48D 2 | 1268 | | S1 → D2C12C19C33C17C31C32C47C18C23C 49C40C34C28C7C21C8C4D28 | 1232 | |
| | D3C10C2C43C39C1C9C22C44C37 C41C26C29C30C36C11C15D3 | 1445 | | S1 → D3C43C39C1C37C41C9C10C2C30C22 C44C26C29C36C11C15D3 | 1487 | |
| R202 | D1 C6C20C16C27C3C38C24C4C25C4 5C3C5C46C14C50C42C13D1 | 1345 | 4346 | S1 → D1C24C38C20C27C3C16C4C13C6C45 C25C5C46C3C14C42C50D1 | 1349 | 4348 |
| | D2C17C32C47C31C49C12C34C40 C18C7C21C19C28C33C23C8C48D 2 | 1156 | | S1 → D2C49C23C34C31C18C33C48C12C7C4 0C17C32C47C21C19C28C8D2 | 1175 | |
| | D3C39C26C29C1C9C37C41C43C3 0C15C22C44C36C10C2C11D3 | 1845 | | S1 → D3C39C22C30C15C26C9C37C11C29C4 1C44C36C1C10C43C2D3 | 1824 | |
| R203 | D1C27C45C3C5C46C3C24C25C50 C4C6C20C14C42C16C13C38D1 | 1467 | 4279 | S1 → D1C3C4C25C45C6C27C24C5C38C42C 3C46C14C50C20C16C13D1 | 1476 | 4159 |
| | D2C40C7C21C12C32C19C33C17C 31C47C18C34C28C23C49C8C48D 2 | 1334 | | S1 → D2C17C19C32C40C21C31C7C33C18C4 9C12C47C28C23C34C8C48D2 | 1354 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | D3C39C1C9C2C22C44C37C41C10 C43C26C29C30C36C11C15D3 | 1478 | | S1 → D3C9C36C11C30C10C1C22C26C41C2 C44C37C43C39C29C15D3 | 1329 | |

**Table 5.35: Scheduling Results for R2**

Table 5.36 presents the results of vehicle routing for the R2 problem. It can be seen in Table 5.36 that objective function value has improved for the three problem instances.

| | | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|---|
| R201 | D1 | S1 → D1C6C20C27C24C25C45C3C3C38C 13C50C4C42C16C5C46C14D1 | 1237 | 3956 | R1 → C24C20C27C6C3C45C25C3C38C50C 5C46C42C16C14C4C13 | 1145 | 3776 |
| | D2 | S1 → D2C12C19C33C17C31C32C47C18C 23C49C40C34C28C7C21C8C4D28 | 1232 | | R1 → C33C32C31C17C19C12C18C47C40C 28C23C7C21C49C34C8C48 | 1265 | |
| | D3 | S1 → D3C43C39C1C37C41C9C10C2C30C 22C44C26C29C36C11C15D3 | 1487 | | R1 → C43C9C10C37C41C39C1C2C44C29C 30C36C22C11C26C15 | 1346 | |
| R202 | D1 | S1 → D1C24C38C20C27C3C16C4C13C6C 45C25C5C46C3C14C42C50D1 | 1349 | 4348 | R1 → C38C20C27C3C6C24C4C13C16C5C5 0C46C45C25C14C42C3 | 1246 | 4399 |
| | D2 | S1 → D2C49C23C34C31C18C33C48C12C 7C40C17C32C47C21C19C28C8D2 | 1175 | | R1 → C49C34C23C48C31C18C12C33C32C 47C19C17C40C7C21C28C8 | 1187 | |
| | D3 | S1 → D3C39C22C30C15C26C9C37C11C2 9C41C44C36C1C10C43C2D3 | 1824 | | R1 → C22C30C2C15C39C37C26C9C11C44 C10C36C1C43C29C41C2 | 1966 | |
| R203 | D1 | S1 → D1C3C4C25C45C6C27C24C5C38C4 2C3C46C14C50C20C16C13D1 | 1476 | 4159 | R1 → C45C4C27C24C6C25C3C5C38 C14C46C50C20C3C16C42C13 | 1545 | 4027 |
| | D2 | S1 → D2C17C19C32C40C21C31C7C33C1 8C49C12C47C28C23C34C8C48D2 | 1354 | | R1 → C33C19C21C17C40C31C32C7C18C2 3C48C12C49C47C34C8C28 | 1228 | |
| | D3 | S1 → D3C9C36C11C30C10C1C22C26C41 C2C44C37C43C39C29C15D3 | 1329 | | R1 → C11 C30C1C22C26C10C9C36 1C2C44C43C37C4C39C29C15 | 1254 | |

**Table 5.36: Routing results for R2**

Table 5.37 presents the results of customer allocation for the C2 problem. It can be seen in Table 5.37 that objective function value has improved for the three problem instances.

| | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| C201 | D1 → C25C45C5C465C14C42C43C3C44C4C6C12C34C3C24 C13C15 | 1134 | 3923 | D1 → C27C3C24C25C45C50C4C6C20C3C5C46C14C42C16C13C38 | 1078 | 3763 |
| | D2 → C31C41C32C47C7C21C22C33C17C18C27C28C23C40C49C8C48 | 1334 | | D2 → C19C33C17C31C12C40C7C21C32C47C18C34C28C23C49C8C48 | 1267 | |
| | D3→ C19C50C26C29C30C1C9C37C20C10C2C36C11C38C16C39 | 1455 | | D3→ C10C2C22C44C26C43C39C1C9C37C41C29C30C36C11C15 | 1418 | |
| C202 | D1 → C24C25C45C4C6C12C34C3C43C5C465C14C42C3C44 C13C15 | 1456 | 3902 | D1 → C6C25C45C3C20C16C27C3C38C24C4C5C46C14C50C42C13 | 1357 | 3765 |
| | D2 → C22C33C17C28C31C41C32C47C18C27C7C21C23C40C49C8C48 | 1323 | | D2 → C31C49C12C32C47C18C34C40C17C7C21C19C28C33C23C8C48 | 1289 | |
| | D3→ C26C2C19C50C36C29C30C1C37C20C10C11C9C38C16C39 | 1123 | | D3→ C39C9C37C41C22C26C29C1C43C30C15C44C36C10C2C11 | 1119 | |
| C203 | D1 → C34C3C24C25C45C5C3C44C4C6C12C465C14C42C43 C13C15 | 1123 | 3811 | D1 → C45C3C5C46C50C4C6C20C27C3C24C25C14C42C16C13C38 | 1109 | 3735 |
| | D2 → C7C21C22C33C17C31C41C32C47C18C27C28C23C40C49C8C48 | 1454 | | D2 → C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48 | 1398 | |
| | D3→ C1C30C36C11C38C9C37C20C10C2C19C50C26C29C16C39 | 1234 | | D3→ C41C10C2C22C43C39C1C9C37C44C26C29C30C36C11C15 | 1228 | |

**Table 5.37: Allocation Results for C2**

Table 5.38 presents the results of customer order scheduling for the C2 problem. It can be seen in Table 5.38 that objective function value has improved for the three problem instances.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| C201 | D1C27C3C24C25C45C50C4C6C20C3C5C46C14C42C16C13C38D1 | 1134 | 4046 | S1 → D1C3C24C25C45C6C20C27C3C38 D1D1C46C14C42C50C4C5C16C13 D1 | 1156 | 3919 |
| | D2C19C33C17C31C12C40C7C21C32C47C18C34C28C23C49C8C48D2 | 1345 | | S1 → D2C33C17C31C19C12C32C47C18 | 1287 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | D2D2C28C23C49C40C7C21C34C8C48D2 | | |
| | D3C10C2C22C44C26C43C39C1C9C37C41C29C30C36C11C15D3 | 1567 | | S1 → D3C43C39C1C9C37C41C10C2D3D3C22C44C26C29C30C36C11C15D3 | 1476 | |
| C202 | D1C6C25C45C3C20C16C27C3C38C24C4C5C46C14C50C42C13D1 | 1388 | 4029 | S1 → D1C27C3C24C38C20C16C4C13C6D1D1C46C45C14C25C3C5C42C50D1 | 1334 | 3800 |
| | D2C31C49C12C32C47C18C34C40C17C7C21C19C28C33C23C8C48D2 | 1365 | | S1 → D2C31C18C49C23C34C33C48C12D2D2C32C47C7C21C40C17C19C28CD28 | 1321 | |
| | D3C39C9C37C41C22C26C29C1C43C30C15C44C36C10C2C11D3 | 1276 | | S1 → D3C15C39C9C22C26C30C37C11C36C1C29C44C10C41C43C2D3 | 1145 | |
| C203 | D1 C45C3C5C46C50C4C6C20C27C3C24C25C14C42C16C13C38D1 | 1156 | 3881 | S1 → D1C24C25C45C4C6C27C3C5C38C14C50C42C46C20C3C16C13D1 | 1112 | 3810 |
| | D2C40C7C21C19C33C17C31C12C32C47C18C34C28C23C49C8C48D2 | 1487 | | S1 → D2C21C17C19C40C31C32C7C33C18C34C28C23C49C12C47C8C48D2 | 1411 | |
| | D3C41C10C2C22C43C39C1C9C37C44C26C29C30C36C11C15D3 | 1238 | | S1 → D3C30C10C9C36C11C1C22C26C39C44C29C37C41C2C43C15D3 | 1287 | |

**Table 5.38: Scheduling Results for C2**

Table 5.39 presents the results of vehicle routing for the C2 problem. It can be seen in Table 5.39 that objective function value has improved for the three problem instances.

| | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| C201 | S1 → D1C3C24C25C45C6C20C27C3C38D1D1C46C14C42C50C4C5C16C13D1 | 1156 | 3919 | R1 → C20C27C6C3C45C24C25C3C38C46C42C16C50C5C14C4C13 | 1023 | 3480 |
| | S1 → D2C33C17C31C19C12C32C47C18D2D2C28C23C49C40C7C21C34C8C48D2 | 1287 | | R1 → C17C19C33C32C31C12C18C47C7C21C40C28C23C49C34C8C48 | 1134 | |
| | S1 → D3C43C39C1C9C37C41C10C2D3D3C22C44C26C29C30C36C11C15D3 | 1476 | | R1 → C41C43C39C9C37C1C10C2C36C22C44C30C11C29C26C15 | 1323 | |
| C202 | S1 → D1C27C3C24C38C20C16C4C13C6D1D1C46C45C14C25C3C5C42C50D1 | 1334 | 3800 | R1 → C27C3C6C24C38C20C4C13C16C45C25C14C5C50C46C42C3 | 1293 | 3548 |
| | S1 → D2C31C18C49C23C34C33C48C12D2D2C32C47C7C21C40C17C19C28CD28 | 1321 | | R1 → C23C48C18C49C34C31C12C33C40C32C21C47C19C7C17C28C8 | 1134 | |
| | S1 → D3C15C39C9C22C26C30C37C11C36C1C29 | 1145 | | R1 → C9C11C22C2C39C26C30C37C15C41 | 1121 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | C44C10C41C43C2D3 | | | C2C44C1C43C29C10C36 | | |
| C203 | S1 → D1C24C25C45C4C6C27C3C5C38C14C50C42C46C20C3C16C13D1 | 1112 | 3810 | R1 → C45C4C27C6C25C3C24C5C38C3C16C14C50C20C46C42C13 | 1084 | 3625 |
| | S1 → D2C21C17C19C40C31C32C7C33C18C34C28C23C49C12C47C8C48D2 | 1411 | | R1 → C32C7C18C33C19C21C17C40C31C23C34C8C48C47C12C49C28 | 1376 | |
| | S1 → D3C30C10C9C36C11C1C22C26C39C44C29C37C41C2C43C15D3 | 1287 | | R1 → C10C9C22C36C11C1C30C26C15C37C41C44C29C2C43C39 | 1165 | |

**Table 39: Routing results for C2**

Table 5.40 presents the results of customer allocation for the RC2 problem. It can be seen in Table 5.40 that objective function value has improved for the three problem instances.

| | Initial solution (NN) | Distance | Total Distance | Final Solution (TS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| RC201 | D1 → C12C34C3C24C25C3C44C4C6C45C5C465C14C42C43 C13C15 | 1192 | 4073 | D1 → C20C27C3C14C42C50C4C6C24C25C45C3C5C46C16C13C38 | 1124 | 3850 |
| | D2 → C31C41C32C47C18C7C21C22C33C17C27C28C23C40C49C8C48 | 1382 | | D2 → C47C40C7C21C19C12C32C33C17C31C18C34C28C23C49C8C48 | 1308 | |
| | D3→ C2C19C50C26C29C1C9C37C20C10C30C36C11C38C16C39 | 1499 | | D3→ C10C2C43C39C1C9C22C44C37C41C26C29C30C36C11C15 | 1418 | |
| RC202 | D1 → C3C44C4C6C12C24C25C45C5C465C14C42C34C3C43C13C15 | 1456 | 4410 | D1 → C6C20C16C27C3C38C24C4C25C45C3C5C46C14C50C42C13 | 1398 | 4174 |
| | D2 → C47C18C27C7C21C31C41C32C22C33C17C28C23C40C49C8C48 | 1387 | | D2 → C17C32C47C31C49C12C34C40C18C7C21C19C28C33C23C8C48 | 1278 | |
| | D3→ C20C36C11C10C2C19C50C26C29C30C1C37C9C38C16C39 | 1567 | | D3→ C39C26C29C1C9C37C41C43C30C15C22C44C36C10C2C11 | 1498 | |
| RC203 | D1 → C4C6C12C34C3C24C25C3C44C45C5C465C14C42C43 C13C15 | 1457 | 4711 | D1 → C27C45C3C5C46C3C24C25C50C4C6C20C14C42C16C13C38 | 1426 | 4525 |
| | D2 → C32C47C18C27C28C7C21C22C33C17C31C41C23C40C49C8C48 | 1678 | | D2 → C40C7C21C12C32C19C33C17C31C47C18C34C28C23C49C8C48 | 1543 | |
| | D3→ C1C9C37C20C10C2C19C50C26C29C30C36C11C38C16C39 | 1576 | | D3→ C39C1C9C2C22C44C37C41C10C43C26C29C30C36C11C15 | 1556 | |

**Table 5.40: Allocation Results for RC2**

Table 5.41 presents the results of order scheduling results for the RC2 problem. It can be seen in Table 5.41 that objective function value has improved for the three problem instances.

| | Initial solution (TS) | Distance | Total Distance | Final Solution (GA) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| **RC201** | **D1C20C27C3C14C42C50C4C6C24C25C45C3C5C46C16C13C38D1** | **1156** | **4179** | **S1 → D1C6C20C27C24C25C45C3C3C38D1C13C50C4C42C16C5C46C14D1** | **1235** | **3872** |
| | **D2C47C40C7C21C19C12C32C33C17C31C18C34C28C23C49C8C48D2** | **1456** | | **S1 → D2C12C19C33C17C31C32C47C18C23C49C40C34C28C7C21C8C48D2** | **1219** | |
| | **D3C10C2C43C39C1C9C22C44C37C41C26C29C30C36C11C15D3** | **1567** | | **S1 → D3C43C39C1C37C41C9C10C2C30C22C44C26C29C36C11C15D3** | **1418** | |
| **RC202** | **D1 → C6C20C16C27C3C38C24C4C25C45C3C5C46C14C50C42C13** | **1434** | **4343** | **S1 → D1C24C38C20C27C3C16C4C13C6C45C25C5C46C3C14C42C50D2** | **1338** | **4265** |
| | **D2 → C17C32C47C31C49C12C34C40C18C7C21C19C28C33C23C8C48** | **1345** | | **S1 → D2C49C23C34C31C18C33C48C12C7C40C17C32C47C21C19C28C8D2** | **1329** | |
| | **D3→ C39C26C29C1C9C37C41C43C30C15C22C44C36C10C2C11** | **1564** | | **S1 → D3C39C22C30C15C26C9C37C11C29C41C44C36C1C10C43C2D3** | **1598** | |
| **RC203** | **D1C27C45C3C5C46C3C24C25C50C4C6C20C14C42C16C13C38D1** | **1455** | **4620** | **S1 → D1C3C4C25C45C6C27C24C5C38C42C3C46C14C50C20C16C13D1** | **1419** | **4485** |
| | **D2C40C7C21C12C32C19C33C17C31C47C18C34C28C23C49C8C48D2** | **1567** | | **S1 → D2C17C19C32C40C21C31C7C33C18C49C12C47C28C23C34C8C48D2** | **1539** | |
| | **D3C39C1C9C2C22C44C37C41C10C43C26C29C30C36C11C15D3** | **1598** | | **S1 → D3C9C36C11C30C10C1C22C26C41C2C44C37C43C39C29C15D3** | **1527** | |

**Table 5.41: Scheduling Results for RC2**

Table 5.42 presents the results of vehicle routing for the RC2 problem. It can be seen in Table 5.42 that objective function value has improved for the three problem instances.

| | Initial solution (GA) | Distance | Total Distance | Final Solution (DS) | Distance | Total Distance |
|---|---|---|---|---|---|---|
| **RC201** | **S1 → D1C6C20C27C24C25C45C3C3C38D1C13C50C4C42C16C5C46C14D1** | **1235** | **3872** | **R1 → D1C24C20C27C6C3C45C25C3C38D1 R2 → D1C50C5C46C42C16C14C4C13D1** | **1287** | **3870** |
| | **S1 → D2C12C19C33C17C31C32C47C18C23C49C40C34C28C7C21C8** | **1219** | | **R1 → D2C33C32C31C17C19C12C18C47D2 D2C40C28C23C7C21C49C34C8C48D2** | **1187** | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | C48D2 | | | | | |
| | S1 → D3C43C39C1C37C41C9C10C2C30C22C44C26C29C36C11C15D3 | 1418 | | R1 → D3C43C9C10C37C41C39C1C2C44C29C30C36C22C11C26C15D3 | 1396 | |
| RC202 | S1 → D1C24C38C20C27C3C16C4C13C6C45C25C5C46C3C14C42C50D2 | 1338 | 4265 | R1 → D1C38C20C27C3C6C24C4C13C16C5C50C46C45C25C14C42C3D1 | 1246 | 4287 |
| | S1 → D2C49C23C34C31C18C33C48C12C7C40C17C32C47C21C19C28C8D2 | 1329 | | R1 → D2C49C34C23C48C31C18C12C33C32C47C19C17C40C7C21C28C8D2 | 1498 | |
| | S1 → D3C39C22C30C15C26C9C37C11C29C41C44C36C1C10C43C2D3 | 1598 | | R1 → D3C22C30C2C15C39C37C26C9C11C44C10C36C1C43C29C41C2D3 | 1543 | |
| RC203 | S1 → D1C3C4C25C45C6C27C24C5C38C42C3C46C14C50C20C16C13D1 | 1419 | 4485 | R1 → D1C45C4C27C24C6C25C3C5C38C14C46C50C20C3C16C42C13D1 | 1438 | 4471 |
| | S1 → D2C17C19C32C40C21C31C7C33C18C49C12C47C28C23C34C8C48D2 | 1539 | | R1 → D2C33C19C21C17C40C31C32C7C18C23C48C12C49C47C34C8C28D2 | 1435 | |
| | S1 → D3C9C36C11C30C10C1C22C26C41C2C44C37C43C39C29C15D3 | 1527 | | R1 → D3C11 C30C1C22C26C10C9C36C1C2C44C43C37C4C39C29C15D3 | 1598 | |

**Table 5.42: Routing results for RC2**

The comparison of the computation times and iterations for allocation, scheduling and routing results for the six problem categories (R1,R2,C1,C2,RC1,RC2) are presented in Table 5.43. It can be seen that all the proposed algorithms for the Customer allocation (NN-TS Search), Order Scheduling (GA approach), and Vehicle routing (Modified Dijkstra's) converge after a finite number of iterations. Also, the computation time is not varying too much due to same number of customers (50) in each of the six problem categories. Moreover, the objective function values have improved for each of the six problem categories (R1,C1,R2,C2,RC1,RC2) using the proposed approaches. This validates the results of our study.

| Problem Type | Problem Number | Allocation | | Scheduling | | Routing | |
|---|---|---|---|---|---|---|---|
| | | Computation Time | Iteration | Computation Time | Iteration | Computation Time | Iteration |
| R1 | R101 | 77 min | 123741 | 33 Min | 537 | 12 Min | 825 |
| | R102 | 83 min | 154875 | 33 Min | 456 | 14 Min | 806 |
| | R103 | 77 min | 123741 | 33 Min | 494 | 12 Min | 692 |
| C1 | C101 | 67 min | 126231 | 33 Min | 510 | 15 Min | 825 |
| | C102 | 71 min | 156716 | 33 Min | 456 | 14 Min | 806 |
| | C103 | 66 min | 123741 | 33 Min | 494 | 13Min | 836 |
| RC1 | RC101 | 89 min | 142040 | 33 Min | 433 | 16 Min | 1100 |
| | RC102 | 62 min | 115766 | 33 Min | 488 | 15 Min | 816 |
| | RC103 | 60 min | 126639 | 33 Min | 519 | 12Min | 646 |
| R2 | R201 | 78min | 123873 | 33 Min | 506 | 12 Min | 1033 |
| | R202 | 83 min | 145785 | 33 Min | 510 | 13 Min | 886 |
| | R203 | 71 min | 126767 | 33 Min | 813 | 12 Min | 833 |
| C2 | C201 | 67 min | 125044 | 33 Min | 466 | 15 Min | 887 |
| | C202 | 71 min | 153926 | 33 Min | 469 | 14 Min | 1111 |
| | C203 | 66 min | 124924 | 33 Min | 473 | 13Min | 665 |
| RC2 | RC201 | 78min | 123873 | 33 Min | 506 | 12 Min | 1033 |
| | RC202 | 83 min | 145785 | 33 Min | 510 | 13 Min | 886 |
| | RC203 | 71 min | 126767 | 33 Min | 813 | 12 Min | 833 |

**Table 5.43: Computation Time and Iteration Results for Results Validation**

## Validation of client allocation

To perform validation for client allocation results, we took the numerical case study presented by Gengui.Z (2003) which is described as follows:

The average transit time (in minutes) between the logistics facilities and the customers is presented as follow

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 |
|---|---|---|---|---|---|---|---|
| Wallingford | 4.48 | 5.83 | 7.90 | 7.33 | 8.08 | 4.18 | 2.11 |
| Ankeny | 15.91 | 14.75 | 12.23 | 12.21 | 12.03 | 15.26 | 19.23 |
| Posen | 10.86 | 9.70 | 7.33 | 7.15 | 6.98 | 10.21 | 15.45 |
| W.Chicago | 11.65 | 10.48 | 8.11 | 7.93 | 7.76 | 11.00 | 16.23 |
| Indianapolis | 9.13 | 7.96 | 4.85 | 5.73 | 6.58 | 8.58 | 14.61 |
| Louisville | 9.41 | 8.25 | 5.30 | 6.18 | 7.11 | 9.01 | 15.06 |
| Boston | 6.48 | 7.40 | 9.91 | 9.33 | 8.73 | 6.20 | 0 |
| Baltimore | 0 | 1.26 | 4.38 | 3.86 | 5.78 | 1.30 | 6.43 |
| Westland | 8.25 | 7.08 | 4.73 | 4.55 | 4.36 | 7.60 | 12.83 |
| Blaine | 17.50 | 16.33 | 13.98 | 13.78 | 13.61 | 16.85 | 18.68 |
| Charlotte | 7.10 | 6.26 | 6.98 | 7.30 | 9.23 | 7.51 | 13.46 |
| Auburn | 7.23 | 8.15 | 10.66 | 1.10 | 9.35 | 6.95 | 1.35 |
| Kenvil | 3.13 | 3.58 | 6.11 | 5.53 | 6.13 | 2.40 | 4.11 |
| Menands | 5.36 | 5.93 | 8.45 | 7.70 | 5.96 | 4.75 | 2.86 |
| Columbus | 6.40 | 5.23 | 2.11 | 3.00 | 3.78 | 5.83 | 11.88 |
| W.Chester | 3.23 | 4.13 | 6.65 | 6.08 | 6.91 | 2.95 | 3.25 |
| Philadelphia | 1.66 | 2.90 | 5.40 | 4.83 | 6.53 | 1.73 | 4.96 |
| Pittsburgh | 3.83 | 2.66 | 1.01 | 0 | 2.11 | 3.18 | 9.23 |
| Nashville | 10.96 | 9.95 | 7.91 | 8.80 | 9.73 | 11.18 | 17.23 |
| Richmond | 2.48 | 2.81 | 5.78 | 5.41 | 7.33 | 3.78 | 8.85 |
| Milwaukee | 12.48 | 11.31 | 8.95 | 8.76 | 8.60 | 11.83 | 17.06 |

**Table 5.44: Average transit time (in minutes) between the depots and clients**

The unit shipping cost (in dollars) between the depots and clients is shown in following table

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 | Demand |
|---|---|---|---|---|---|---|---|---|
| Wallingford | 2.9 | 3.2 | 3.5 | 3.14 | 3.15 | 3.0 | 2.1 | 113644 |
| Ankeny | 3.9 | 4.0 | 4.3 | 3.62 | 3.60 | 4.1 | 5.8 | 25360 |
| Posen | 3.5 | 3.6 | 3.5 | 3.14 | 3.12 | 3.6 | 4.8 | 82507 |
| W.Chicago | 3.5 | 3.6 | 3.6 | 3.19 | 3.17 | 3.6 | 4.9 | 80159 |
| Indianapolis | 3.3 | 3.4 | 3.0 | 2.99 | 3.07 | 3.4 | 4.6 | 75274 |
| Louisville | 3.3 | 3.4 | 3.1 | 3.04 | 3.13 | 3.5 | 4.7 | 116064 |
| Boston | 3.1 | 3.3 | 3.8 | 3.31 | 3.28 | 3.2 | 1.8 | 32263 |
| Baltimore | 2.5 | 2.9 | 3.0 | 2.83 | 3.00 | 2.7 | 3.0 | 162106 |
| Westland | 3.2 | 3.3 | 3.0 | 2.88 | 2.86 | 3.3 | 4.1 | 151417 |
| Blaine | 4.0 | 4.1 | 4.6 | 3.76 | 3.74 | 4.2 | 6.1 | 40833 |
| Charlotte | 3.1 | 3.3 | 3.4 | 3.10 | 3.28 | 3.3 | 4.4 | 97758 |
| Auburn | 3.1 | 3.4 | 4.0 | 3.38 | 3.24 | 3.2 | 2.0 | 63643 |
| Kenvil | 2.8 | 3.0 | 3.2 | 2.95 | 3.04 | 2.8 | 2.5 | 367379 |
| Menands | 3.0 | 3.2 | 3.6 | 3.18 | 3.03 | 3.0 | 2.3 | 276387 |
| Columbus | 3.1 | 3.2 | 2.6 | 2.74 | 2.82 | 3.2 | 4.1 | 85180 |
| W.Chester | 3.2 | 3.3 | 2.8 | 2.88 | 2.97 | 3.3 | 4.4 | 79662 |
| Philadelphia | 2.7 | 3.0 | 3.1 | 2.92 | 3.05 | 2.8 | 2.7 | 122560 |
| Pittsburgh | 2.9 | 3.0 | 2.4 | 2.47 | 2.65 | 2.9 | 3.5 | 106198 |
| Nashville | 3.5 | 3.6 | 3.5 | 3.30 | 3.38 | 3.7 | 5.2 | 57305 |
| Richmond | 2.7 | 3.0 | 3.2 | 2.96 | 3.14 | 3.0 | 3.5 | 119524 |
| Milwaukee | 3.6 | 3.7 | 3.8 | 3.28 | 3.27 | 3.7 | 5.1 | 60096 |

**Table 5.45: Unit shipping cost (in dollars) and demand (in units of products)**

We are using nearest neighborhood and tabu search algorithm for allocating the clients to depots and .

In Gengui.Z (2003) paper, they propose 7 Pareto optimal solutions. We have considered all 7 solution for comparison with our model results. The meta-heuristics were run for 12000 iterations and the results obtained are presented in below. It can be seen the hybrid approach of nearest neighborhood and tabu search perform better than the results of Gengui.Z (2003) in terms of transit time and cost.

| | 1 | 2 | 3 | Transit time |
|---|---|---|---|---|
| Depots 1 | Philadelphia | Richmond | Milwaukee | 16.62 |
| Depots 2 | Charlotte | Pittsburgh | Nashville | 18.87 |
| Depots 3 | Indianapolis | Louisville | Columbus | 12.26 |
| Depots 4 | Westland | Blaine | Auburn | 19.43 |
| Depots 5 | Ankeny | Posen | W.Chicago | 26.77 |
| Depots 6 | Baltimore | Kenvil | W.Chester | 6.65 |
| Depots 7 | Wallingford | Boston | Menands | 4.97 |
| Total transit time | | | | 105.57 |

**Table 5.46: Allocation results by NN and Tabu search**

Also based on demand for each city and related cost we can calculate the total cost based on related demands as following:

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 |
|---|---|---|---|---|---|---|---|
| Wallingford | 329,567.60 | 363,660.80 | 397,754.00 | 356,842.16 | 357,978.60 | 340,932.00 | 238,652.40 |
| Ankeny | 98,904.00 | 101,440.00 | 109,048.00 | 91,803.20 | 91,296.00 | 103,976.00 | 147,088.00 |
| Posen | 288,774.50 | 297,025.20 | 288,774.50 | 259,071.98 | 257,421.84 | 297,025.20 | 396,033.60 |
| W.Chicago | 280,556.50 | 288,572.40 | 288,572.40 | 255,707.21 | 254,104.03 | 288,572.40 | 392,779.10 |
| Indianapolis | 248,404.20 | 255,931.60 | 225,822.00 | 225,069.26 | 231,091.18 | 255,931.60 | 346,260.40 |
| Louisville | 383,011.20 | 394,617.60 | 359,798.40 | 352,834.56 | 363,280.32 | 406,224.00 | 545,500.80 |
| Boston | 100,015.30 | 106,467.90 | 122,599.40 | 106,790.53 | 105,822.64 | 103,241.60 | 58,073.40 |
| Baltimore | 405,265.00 | 470,107.40 | 486,318.00 | 458,759.98 | 486,318.00 | 437,686.20 | 486,318.00 |
| Westland | 484,534.40 | 499,676.10 | 454,251.00 | 436,080.96 | 433,052.62 | 499,676.10 | 620,809.70 |
| Blaine | 163,332.00 | 167,415.30 | 187,831.80 | 153,532.08 | 152,715.42 | 171,498.60 | 249,081.30 |
| Charlotte | 303,049.80 | 322,601.40 | 332,377.20 | 303,049.80 | 320,646.24 | 322,601.40 | 430,135.20 |
| Auburn | 197,293.30 | 216,386.20 | 254,572.00 | 215,113.34 | 206,203.32 | 203,657.60 | 127,286.00 |
| Kenvil | 1,028,661.20 | 1,102,137.00 | 1,175,612.80 | 1,083,768.05 | 1,116,832.16 | 1,028,661.20 | 918,447.50 |
| Menands | 829,161.00 | 884,438.40 | 994,993.20 | 878,910.66 | 837,452.61 | 829,161.00 | 635,690.10 |
| Columbus | 264,058.00 | 272,576.00 | 221,468.00 | 233,393.20 | 240,207.60 | 272,576.00 | 349,238.00 |
| W.Chester | 254,918.40 | 262,884.60 | 223,053.60 | 229,426.56 | 236,596.14 | 262,884.60 | 350,512.80 |
| Philadelphia | 330,912.00 | 367,680.00 | 379,936.00 | 357,875.20 | 373,808.00 | 343,168.00 | 330,912.00 |
| Pittsburgh | 307,974.20 | 318,594.00 | 254,875.20 | 262,309.06 | 281,424.70 | 307,974.20 | 371,693.00 |
| Nashville | 200,567.50 | 206,298.00 | 200,567.50 | 189,106.50 | 193,690.90 | 212,028.50 | 297,986.00 |
| Richmond | 322,714.80 | 358,572.00 | 382,476.80 | 353,791.04 | 375,305.36 | 358,572.00 | 418,334.00 |
| Milwaukee | 216,345.60 | 222,355.20 | 228,364.80 | 197,114.88 | 196,513.92 | 222,355.20 | 306,489.60 |

**Table 5.47: Demand costs**

Following table shows comparison of the results of our approach proposed and Gengui.Z (2003) approach results. Our solution approach ware run for 9000 iterations and it shown our solution based on NN and tabu search have better performance in terms of transit time and shipping costs than average of different Pareto solutions by Gengui.Z (2003).

| **Pareto solutions** | **Total shipping cost (Gengui.Z)** | **Total shipping cost ($)** | **Total transit time (Gengui.Z)** | **Total transit time (h)** |
|---|---|---|---|---|
| 1 | 7,946,066.93 | 6,593,750.35 | 124.89 | 105.57 |

**Table 5.48: Transit time and delivery costs**

**Comparison of route planning with TSP**

In the Traveling Salesman Problem (TSP), the goal is to find the shortest distance between *N* different cities. The path that the salesman takes is called a tour.

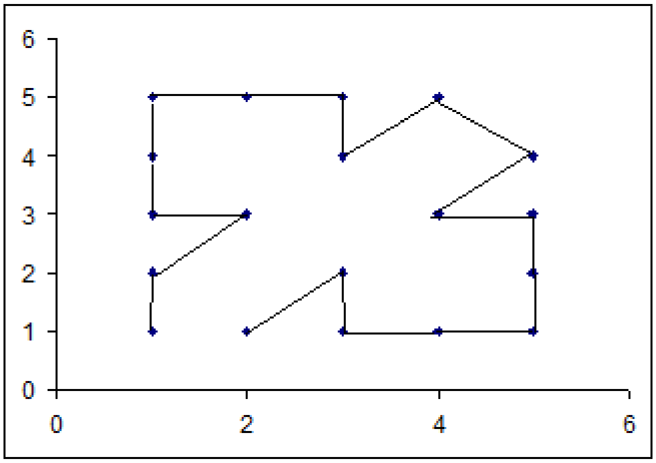
To compare our approach based on modified Djikstra algorithm to the Travelling Salesman Problem (TSP), we took the numerical case study presented by Wolfram (2012) as follows. Here X and Y are the position coordinates of each city.

| | X | Y |
|---|---|---|
| A | 1 | 2 |
| B | 1 | 2 |
| C | 1 | 3 |
| D | 1 | 4 |
| E | 1 | 5 |
| F | 2 | 1 |

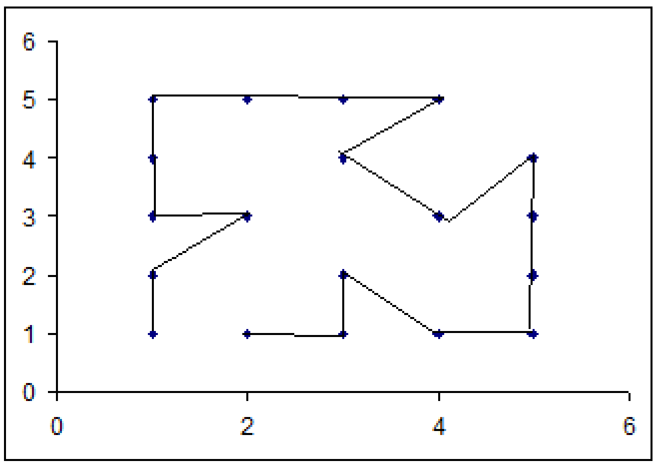
| | | |
|---|---|---|
| G | 2 | 3 |
| H | 2 | 5 |
| I | 3 | 1 |
| J | 3 | 2 |
| K | 3 | 4 |
| L | 3 | 5 |
| M | 4 | 1 |
| N | 4 | 3 |
| O | 4 | 5 |
| P | 5 | 1 |
| Q | 5 | 2 |
| S | 5 | 3 |
| T | 5 | 4 |

Following table shows the comparison of our results with that of Wolfram (2012). Our solution approach was based on modification of Dijkstra algorithm in terms of finding the fastest path. We also changed our objective function to calculating only distances in order to compare our results to the results from Wolfram.

| Wolfram (2012) Route | Route | Total Distance Wolfram (2012) | Total Distance |
|---|---|---|---|
| *A-B-G-C-D-E-H-L-K-O-T-N-S-Q-P-M-I-J-F* | *A-B-G-C-D-E-H-L-O-K-N-T-S-Q-P-M-J-I-F* | 21.07 | 20.98 |




*Wolfram Result*




*Modified Djikstra Result*

**Comparison of the computational time for R1, C1, RC1,….. problems.**

The computation times can be tested on a classic benchmark problem (the Solomon's problem) to measure the performance of our algorithm in terms of speed and quality of the solutions. The solution was run on a Pentium IV 2.66 GHz for 10 problem in each group (R1,C1,..) and the total computation times is considered. A comparison of computing time for finding optimal solution is made between the solutions obtained by our solution approach to the ones obtained by

Jinxia X. (2010) and Alberto V. (2003). The comparative results are shown in the following table:

| Problems | R1 | C1 | RC1 | R2 | C2 | RC2 |
|---|---|---|---|---|---|---|
| Time(s) | 630 | 730 | 525 | 660 | 423 | 485 |
| Alberto V(2003) | 1800 | 1800 | 1800 | 1800 | 1800 | 1800 |
| Jinxia X. (2010) | 650 | 490 | 570 | 590 | 460 | 530 |

**Table 5.49: Comparative table results**

# Chapter 6:

# Decision Support System for Goods distribution planning

In this chapter we propose a prototype decision support system for good distribution planning based on the proposed approaches for client allocation to different depots, scheduling of customer orders and generation of delivery vehicle routes while minimizing travel time and costs. Figure 6.1 presents a snapshot of the main screen of the developed Decision Support System.

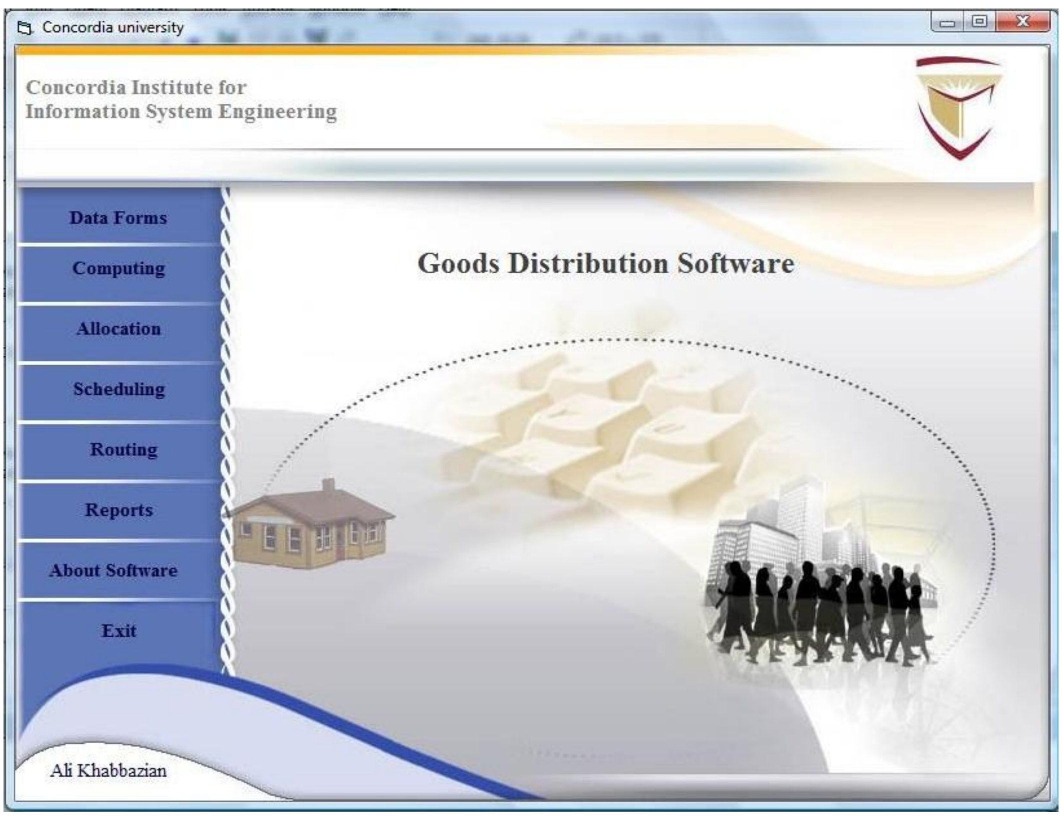



**Figure 6.1: schematic view of the software interface**

### 6.2 System Overview

Figure 6.2 presents the main components of the proposed DSS. It can be seen that there is a). Central Database which is includes the all depots and client information in ERP environment. b). Local Database for each single depot.  c). User Interface d). Mainframe e). Web Server.

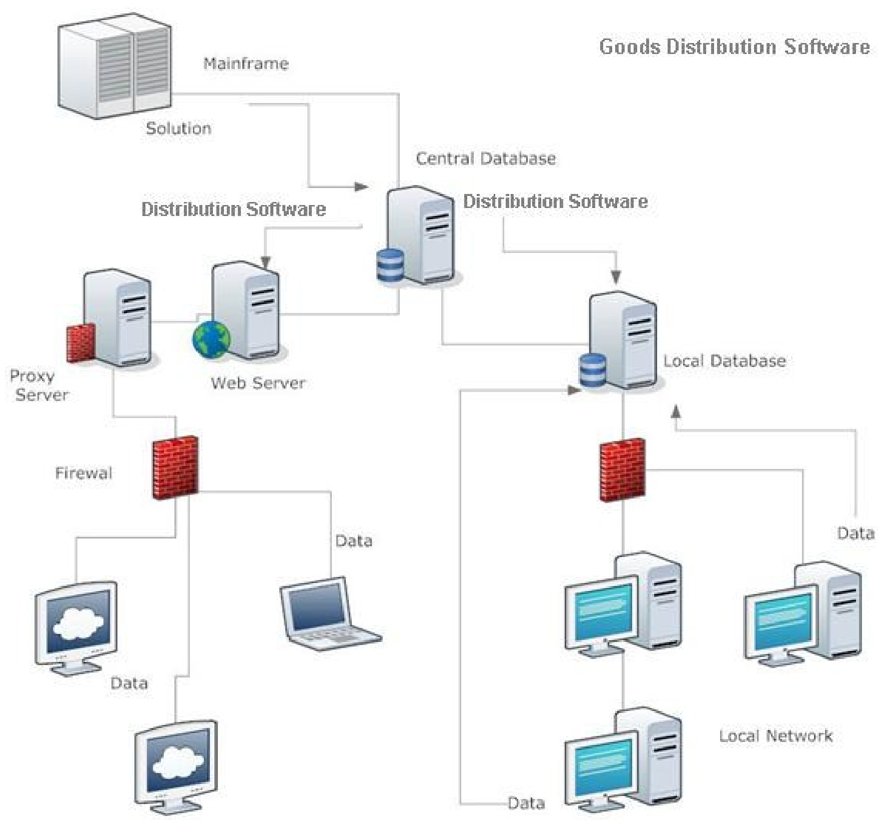



**Figure 6.2: Schematic view of the software system**

### 6.3 Product Features

The proposed DSS is a Windows-based Processing and Document Management software. Big scale companies can create unlimited users (customer) that have secured access anywhere /

anytime to all features of the system. Users can easily create a new project and deliver it to any depot in the world. In addition to creating this type of automation, companies can realize a tremendous cost benefit by reducing their branches. Table 6.1-6.2 present the proposed software features and area description.

| FEATURES | BENEFITS |
|---|---|
| **Unlimited Project definition** | **We can have unlimited project in this system and each one can control individually and they can use in the future for other new companies.** |
| **Web Based** | **Access branch files anytime / anywhere using any PC with an internet connection.** |
| **Unique file number** | **Each depot can have an ID number and they can have so many reports based on that.** |
| **Monitoring** | **Monitor companies' on-going requests (graphical view of the processing circuit** |
| **Switch between processes** | **Switch between all-processes and single-process views** |

**Table 6.1: Software features and benefits**

| AREA | DESCRIPTION |
|---|---|
| Transaction Volume | Number of discrete transactions (receipts, puts, internal moves, transfers, picks and shipments per hour, shift, day) at peak. |
| Number of Users | Number of personnel who will be interacting including warehouse staff, customer service, administration and management. |
| Data Entry Devices | Number of project that define in the system |
| Systems Interfaces | Host and other systems interfaces, anticipated transaction frequency. |
| Response Times | Expected amount of time that will take to process the calculated distribute system. |

**Table 6.2: Software features description**

### 6.4 System Functions

The main functions of the system can be summarized as:

- Add new project;
- Add new matrix of depot and customer;
- Define chart;
- Define factors for calculation;
- Search between old projects with all result;
- Delete project;
- Edit project and compute new result based on edition;
- Follow up result step by step.

Figure 6.3 shows a class diagram describing the system's classes, their attributes, operations and the relations.

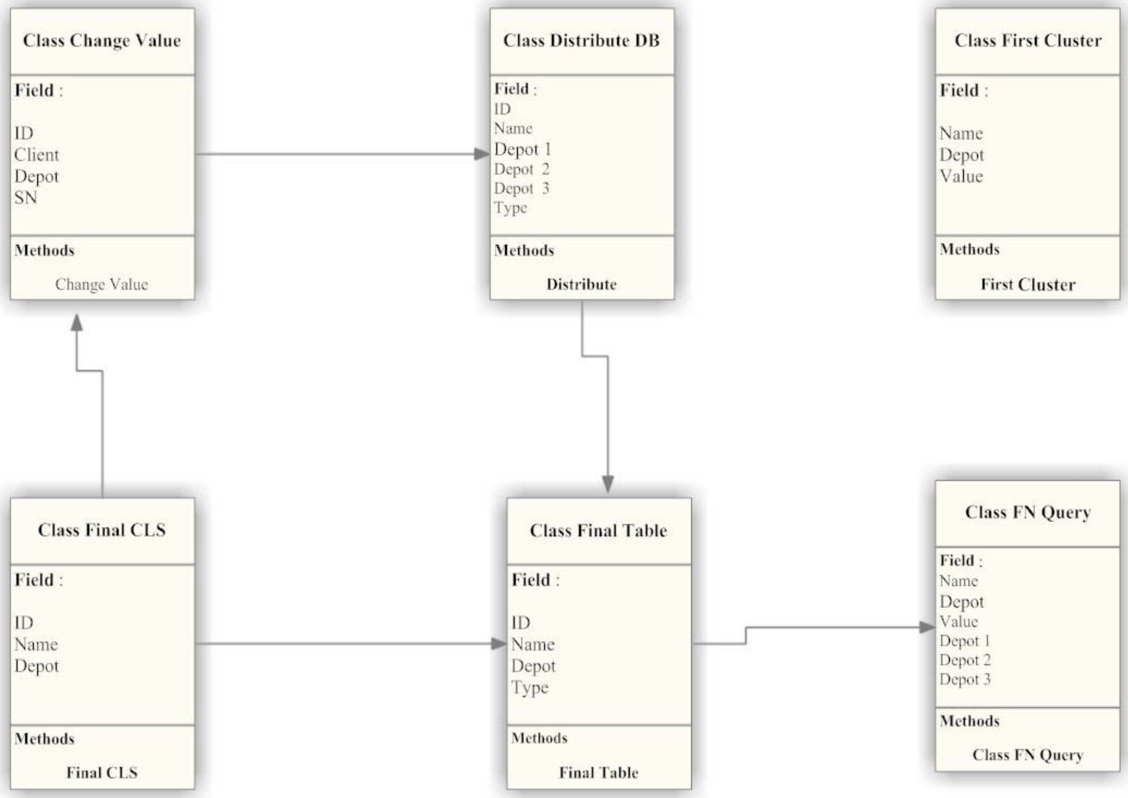



**Figure 6.3: Simple class diagram of the system**

## 6.5 Non-functional Requirements

### 6.5.1 User Classes and Characteristics

**Administrators**

These users control, enable, disable the reporting capability. The project level activation will most likely be done by the Project Owner. They will be in a position to permit access to the system in the report and acknowledge the result status. They can also get the overall report of the project sessions. Administrators can permit users to access the report and resources. They can also view in real time what the result is for each single project.

**Client Users**

They login at the client level to get access to their projects. They can also view their report's status in the client system just for one project.

**Project Supporter**

These users are responsible for configuring the reports and maintaining and defining the software reports. They will also be allowed to enable/disable reporting at the project level.

**Project Users**

These users will be viewing the configured reports. They may also be allowed to pass parameters to the report configuration and run it, but will not be allowed to save to the software.

All members of the project are potentially this type of user.

### 6.5.2 Operating Environment

Client System and Operating System are Windows2000 Prof/Linux and Processor Pentium 4, 1.2GHz Pentium4, 2GHz ,Hard disk 40GB 100GB ,RAM 256MB 512MB , and the web version will be run on an IIS 5.0 web server. The database is MS SQL Server 2008. The system will be developed in MS Windows 7 with Visual Studio 2008. Figure 6.4 shows the systems view of the proposed DSS.

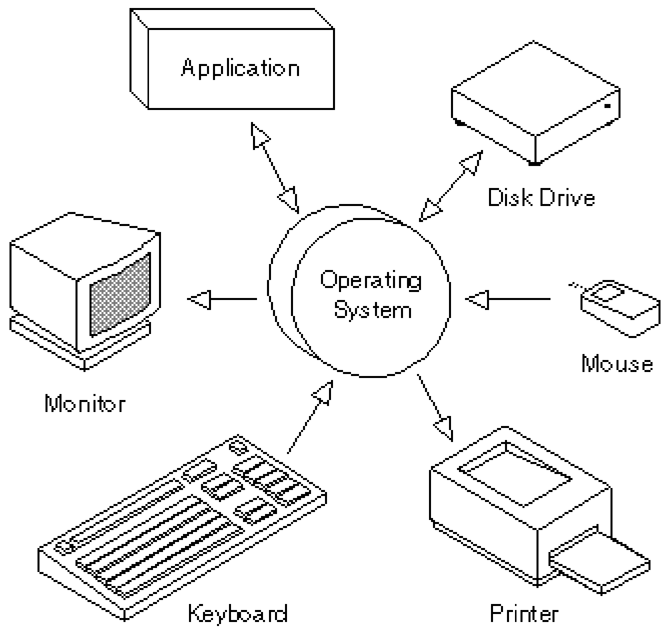



**Figure 6.4: System components**

### 6.5.3 Design and Implementation Constraints

Each user must keep their password confidential. Moreover, the user must have individual ID for creating a login in the system. Only the administrator can control user addition and deletion in the system. Also this group could only create reports.

### 6.5.4 User Documentation

The product is under development stage and requires a complete implemented prototype to explain the user documentation. Once the prototype is designed and implemented, online manuals and user manuals can be provided.

### 6.5.5 Assumptions and Dependencies

- Only two locations are connected to the system.
- Each location is always connected.
- Each User must have a User ID and password.
- There is only one Administrator.
- Central Database must always be accessible under Windows system.
- Proper component should be installed to run the software.
- Text readers should be installed to view the help files.

### 6.5.6 Performance Requirements

The proposed DSS should be fast and efficient in performing the allocation, scheduling and routing operations. Under large datasets, speed of calculation becomes a vital feature.

### 6.5.7 Safety Requirements

The data handled in the Distribution System Allocation system is very vital. The server should always be confirmed to run properly and the data are saved to the database at consecutive intervals. Calculation is a significant feature and the formula for calculation should always be taken care of.

### 6.5.8 Security Requirements

The security system features having a login for all the users to access the software. The login details will also be used in the system. Therefore, the chances of the software getting intruded are very small.

### 6.5.9 Special user requirements

**Backup and recovery**

a. Keep backups of all data files in a separate directory/drive.

b. Frequently auto-save information, in case of a lost network connection, the browser or the system crashing, etc.

**Data migration**

The concept of data migration is important to ensure that the data that is being entered and stored today could be accessed even after several years.

**User training**

Clients must be trained to operate the Goods Distribute System software in creating new project and performing reports.

## 6.6 Validating the System Architecture

To validate the system architecture, we developed a number of use cases. A Use case is a list of steps, typically defining interactions between a role and a system, to achieve a goal. The actors in GDS are customer service, shipping staff and depots. Figure 6.5 presents a use case diagram for the proposed decision support system.

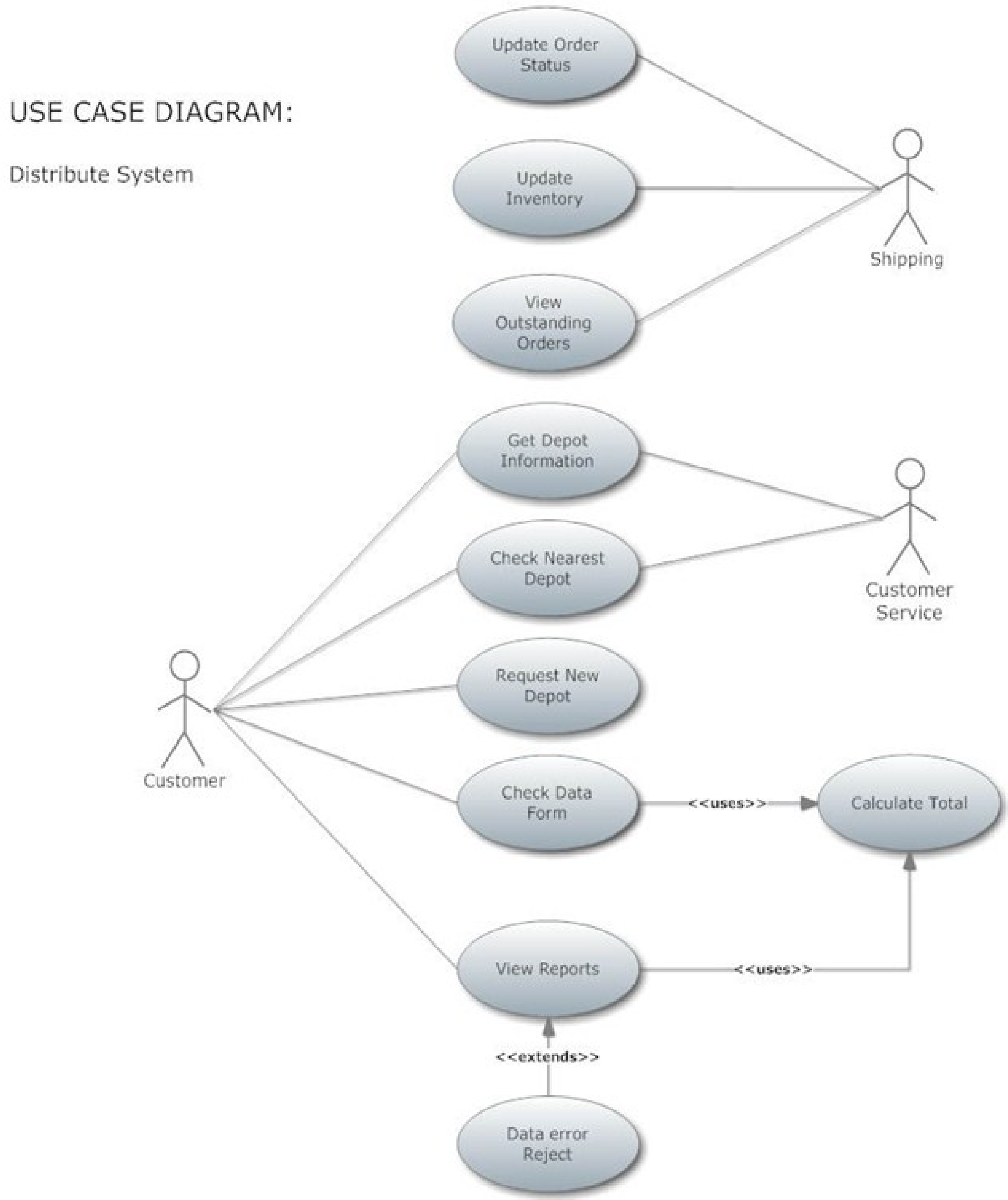



**Figure 6.5: Use Case Diagram**

List of use cases and the actors are presented in Tables 6.3.

| Primary Actor | Use Cases |
|---|---|
| Custom | 1. Authentication<br>2. Monitoring<br>3. Calculability<br>4. Add Data Project<br>5. Add Depot<br>6. Add Client<br>7. Add Report |
| Shipping | Add Client Location |
| Customer service (Admin ) | Check nearest Depot |

**Table 6.3: Use Cases and actors list**

The details of the 7 Use Cases listed above are provided as follows:

| | |
|---|---|
| Use Case ID: | 1 |
| Use Case Name: | **Authentication** |
| Actors: | Custom |
| Description: | 1. A Custom must be Authenticate to the system. |
| Preconditions: | 1. Project ID must be determined.<br>2. Project name must be determined.<br>3. Project does not already exist in the system. |
| Post conditions: | 1. A project record should be added to the system. |
| Normal Flow: | Authentication<br>User enters project ID.<br>User enters project name.<br>User submits the data to the server. |
| Exceptions: | 1. Project Record Exists in the System |
| Includes: | None |
| Priority: | High |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | None |
| Assumptions: | None |
| Notes and Issues: | None |

### 6.6.1 Authentication

**Description and Priority**

Description and Priority: the system offers access to reports at client level and access to server resources at admin level only by validating the user with the unique username and password.

**Stimulus/Response Sequences**

The response/stimulus for the different classes of users are:

1) Users: - Login.

2) Administrator: Adding new project, giving final reports, getting & sending basic reports.

**Functional Requirements**

All systems should have the Project ID number for program running. The server should identify individual systems by their name.

Input: User name and password, Account number

Output: Access to project, Available Reports, project Details.

### 6.6.2 Monitoring

| | |
|---|---|
| Use Case ID: | 2 |
| Use Case Name: | **Monitoring** |
| Actors: | Custom |
| Description: | A Custom must be monitoring the system. |
| Preconditions: | Project ID must be Monitor. |
| Post conditions: | A project record should exist on the system. |
| Normal Flow: | **Monitoring**<br><br>User enters project ID.<br>User enters project name |
| Exceptions: | project Record Exist in the System |
| Includes: | None |
| Priority: | High |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | None |
| Assumptions: | None |
| Notes and Issues: | None |

**Description and Priority**

This utility is used to monitor the project status of the various companies using the system.

**Stimulus/response sequences**

The response/stimulus for the different classes of users are:

1) Administrator: Login, View Accounts, View real time project reports.

**Functional requirements**

All projects should have the ID for project running. The server should identify individual project by their ID and name.

Input: User name and password, Project number

Output: Project Reports, Project Details.

### 6.6.3 Calculability

| | |
|---|---|
| Use Case ID: | 3 |
| Use Case Name: | **Calculability** |
| Actors: | Custom |
| Description: | A system must be Calculate the values like client distance. |
| Preconditions: | Project features must be calculated. |
| Post conditions: | A project record should exist to the system. |
| Normal Flow: | Calculability<br>1. User enters project ID.<br>2. User enters project name |
| Exceptions: | **project Record Exist in the System** |
| Includes: | None |
| Priority: | High |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | None |
| Assumptions: | None |
| Notes and Issues: | None |

**Description and Priority**

This module is designed to support the user accounts in the software. Only the administrators could access this.

**Stimulus/response sequences**

The response/stimulus for the different classes of users are:

Administrator: Login, View and calculate new allocation, Create real time reports.

**Functional requirements**

All system should have the Project ID number for program running. The server should identify individual systems by their name.

Input: User name and password, depot number

Output: Access to project, Available Reports, project Details.

### 6.6.4 Add Data Project

| | |
|---|---|
| Use Case ID: | 4 |
| Use Case Name: | **Add Data Project** |
| Actors: | Custom |
| Description: | A Custom must be entering the new Data to the system. |
| Preconditions: | 1. Project ID must be created.<br>2. Project name must be created. |
| Post conditions: | A project record should be added to the system. |
| Normal Flow: | Add Data<br>User enters project ID.<br>User enters project Data.<br>User submits the data to the server. |
| Exceptions: | 1. project Record Exist in the System |
| Includes: | None |
| Priority: | Low |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | Project ID |
| Assumptions: | None |
| Notes and Issues: | None |

**Description and Priority**

This module is designed to support the user entering new project Data in the software. All users and the administrators could access this.

**Stimulus/response sequences**

The response/stimulus for the different classes of users is:

Administrator: View and control new Data, Create real time reports of new data.

**Functional requirements**

All systems should have the Project ID number for program running. The server should identify individual systems by their name.

Input: project data, depot number

Output: Access to project, Available Reports, project Details.

### 6.6.5 Add Depot

| | |
|---|---|
| Use Case ID: | 5 |
| Use Case Name: | **Add Depot** |
| Actors: | Custom , Admin |
| Description: | A Custom must be entered in the new Depot of the system. |
| Preconditions: | Depot ID must be created.<br>Depot name must be created. |
| Postconditions: | A project record should be added to the system. |
| Normal Flow: | **Add Depot**<br>User enters Depot ID.<br>User enters Depot Data.<br>User submits the data to the server. |
| Exceptions: | 1. Depot Exist in the System |
| Includes: | None |
| Priority: | Low |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | Project ID |
| Assumptions: | None |
| Notes and Issues: | None |

**Description and Priority**

This module is designed to support the user and to create new depot in the software. All users and the administrators could access this.

**Stimulus/response sequences**

The response/stimulus for the different classes of users is:

Administrator: View and control new depot, Create real time reports of new depot.

**Functional requirements**

All systems should have the depot ID number for program running. The server should identify individual systems by their name.

Input: depot data, depot ID

Output: Access to project, Available Reports, project Details.

### 6.6.6 Add Report

| | |
|---|---|
| Use Case ID: | 6 |
| Use Case Name: | **Add Report** |
| Actors: | Administrator |
| Description: | A Custom must enter the new Depot to the system. |
| Preconditions: | Report form must be created.<br>Report name must be created.<br>Report detail must be designed. |
| Post conditions: | A project record should be added to the system. |
| Normal Flow: | Add Report<br>Admin enters Report ID.<br>Admin enters Report detail.<br>Admin design new report and submit it to the system. |
| Exceptions: | 1. project Record Exist in the System |
| Includes: | None |
| Priority: | High |
| Frequency of Use: | |
| Business Rules: | None |
| Special Requirements: | Project ID , design |
| Assumptions: | None |
| Notes and Issues: | None |

**Description and Priority**

This module is designed to support the user to have new reports to improve the software. Only administrators could access this.

**Stimulus/response sequences**

The response/stimulus for the different classes of users are:

Administrator: Design, View and control new Report, Create real time new Report.

**Functional requirements**

All systems should have the depot ID number for program running. The server should identify individual systems by their name.

Input: Design Report, Report Name

Output: Access to new report, Report Details.

## 6.7 Verifying the system architecture

To verify the architecture of the proposed DSS, we developed System Sequence Diagram. A System sequence diagram (SSD) shows a particular scenario of a use case, the events that external actors generate, their order, and possible inter-system events. Figure 6.6-6.11 present the various sequence diagrams associated with the proposed DSS.

### 6.7.1 Authentication

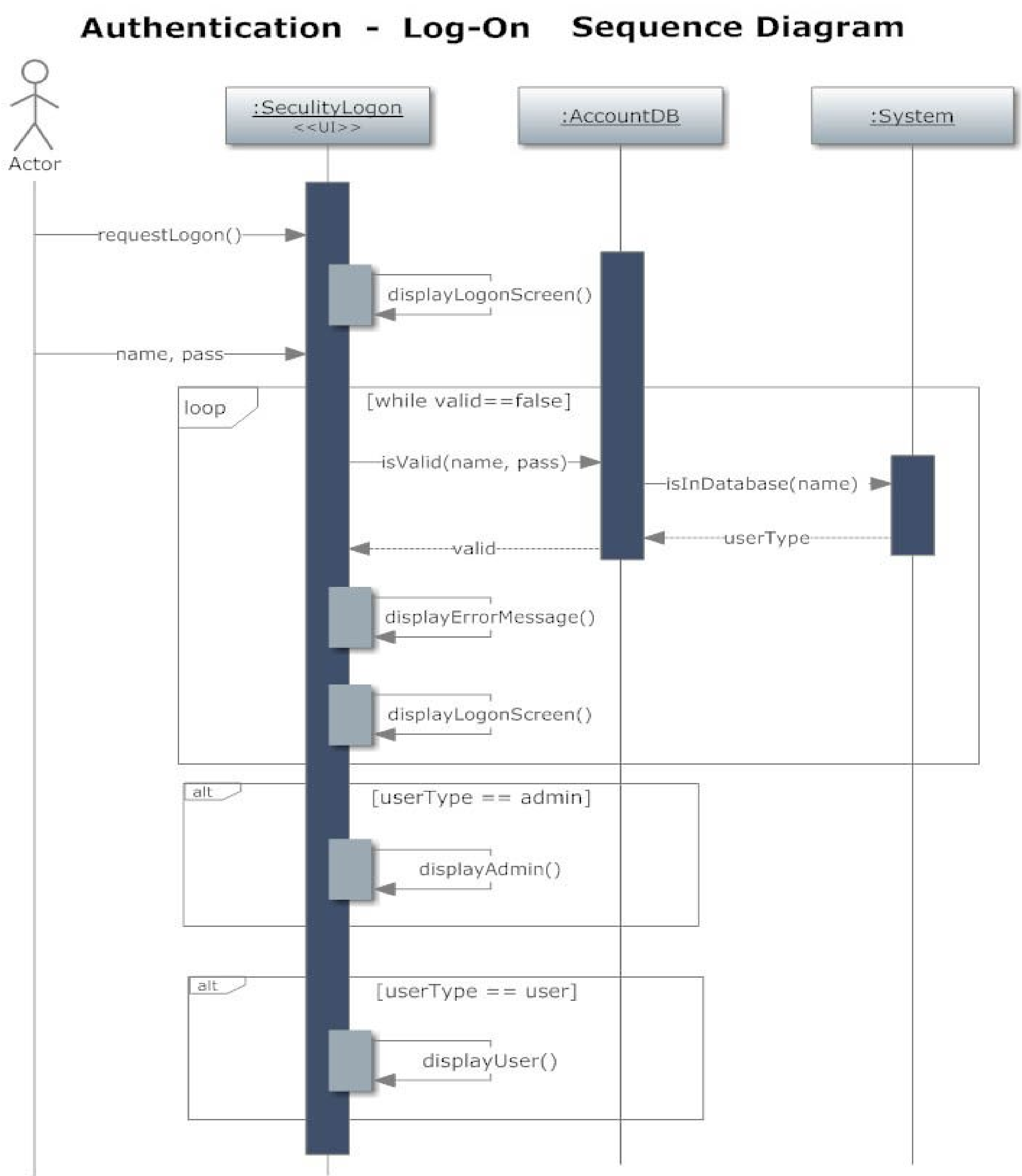



**Figure 6.6 :Authentication sequence diagram**

### 6.7.2 Monitoring

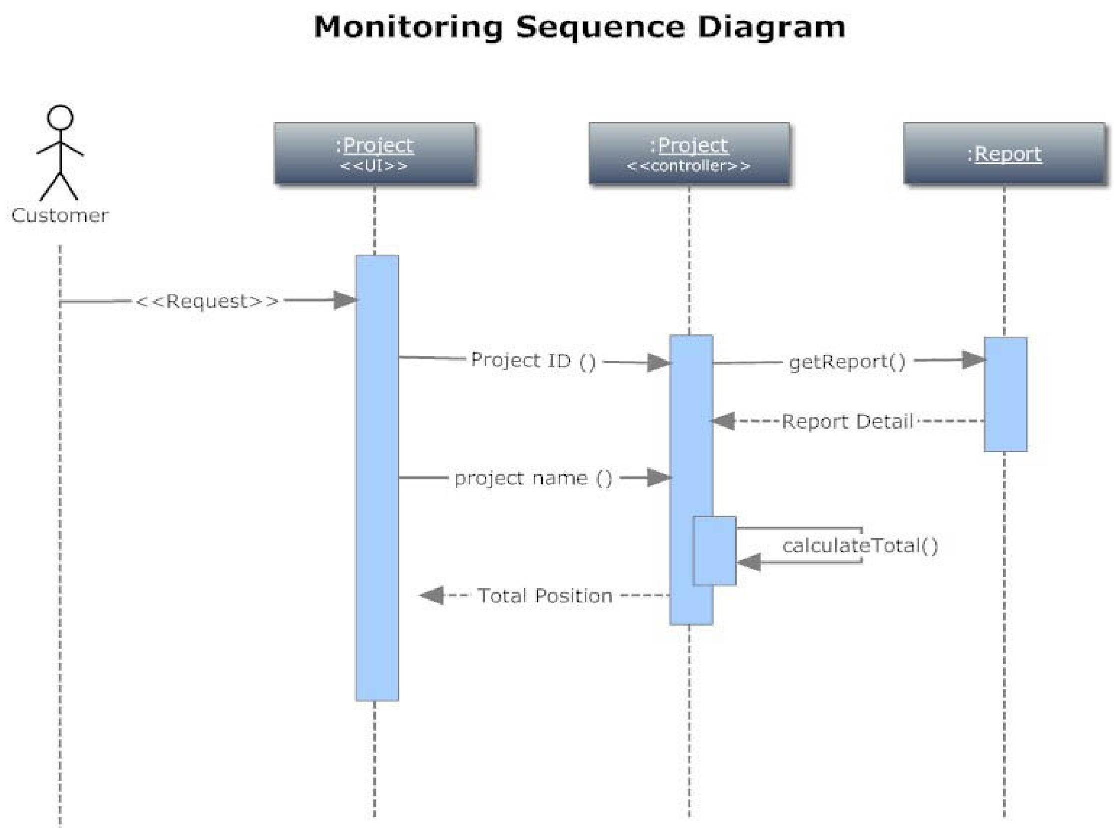



**Figure 6.7 :Monitoring sequence diagram**

### 6.7.3 Calculability

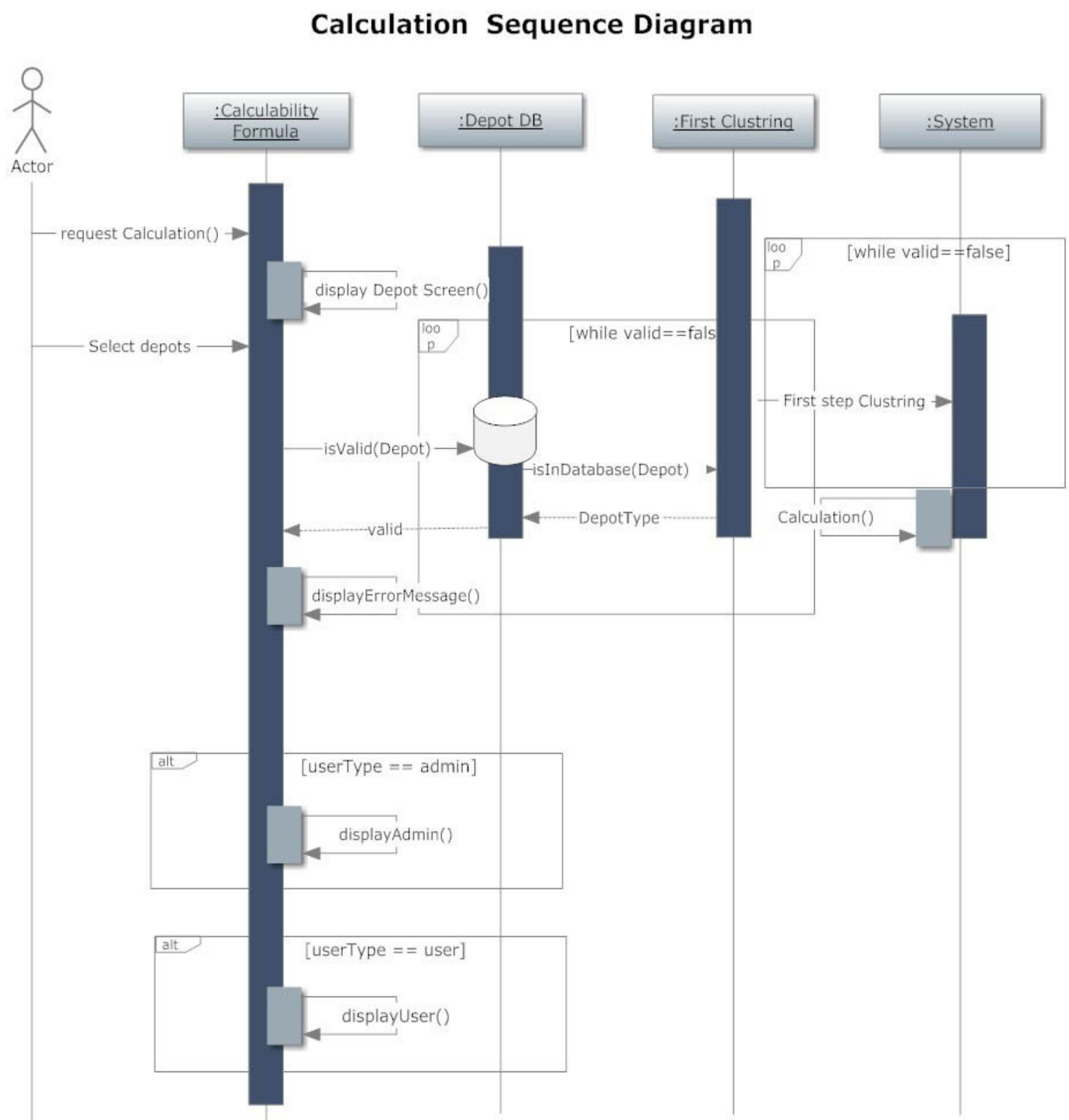



**Figure 6.8: Calculation sequence diagram**

### 6.7.4 Add Data Project

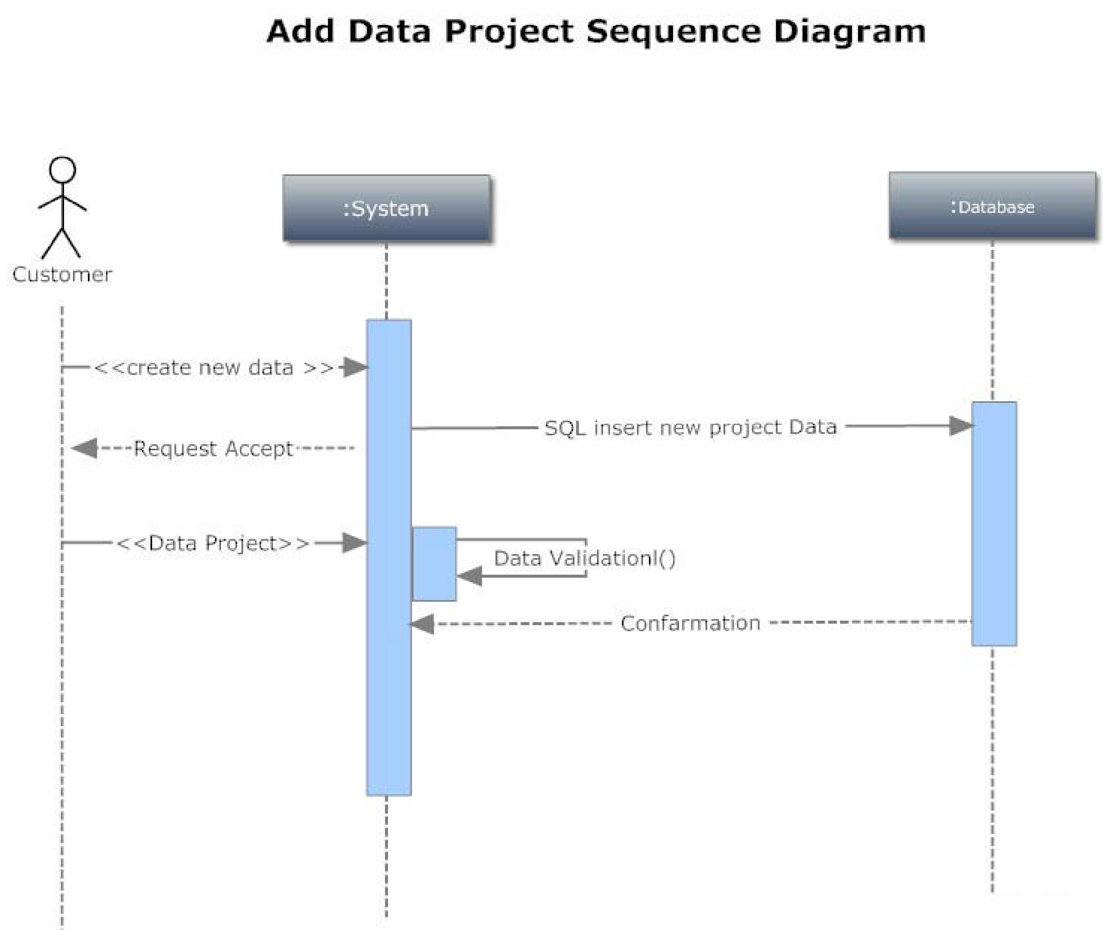



**Figure 6.9: Add project sequence diagram**

### 6.7.5 Add Depot

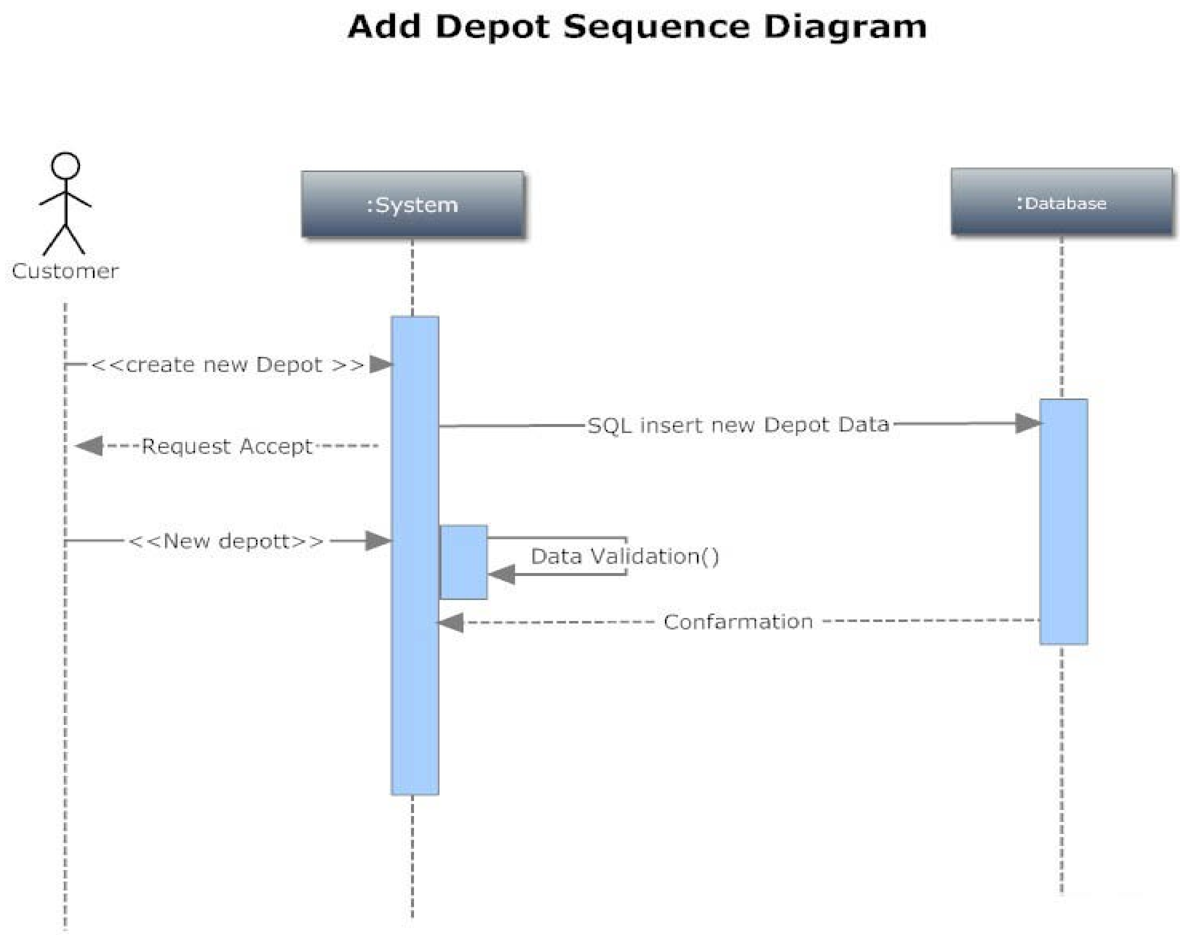



**Figure 6.10: Add Depot sequence diagram**

### 6.7.6. Add Report

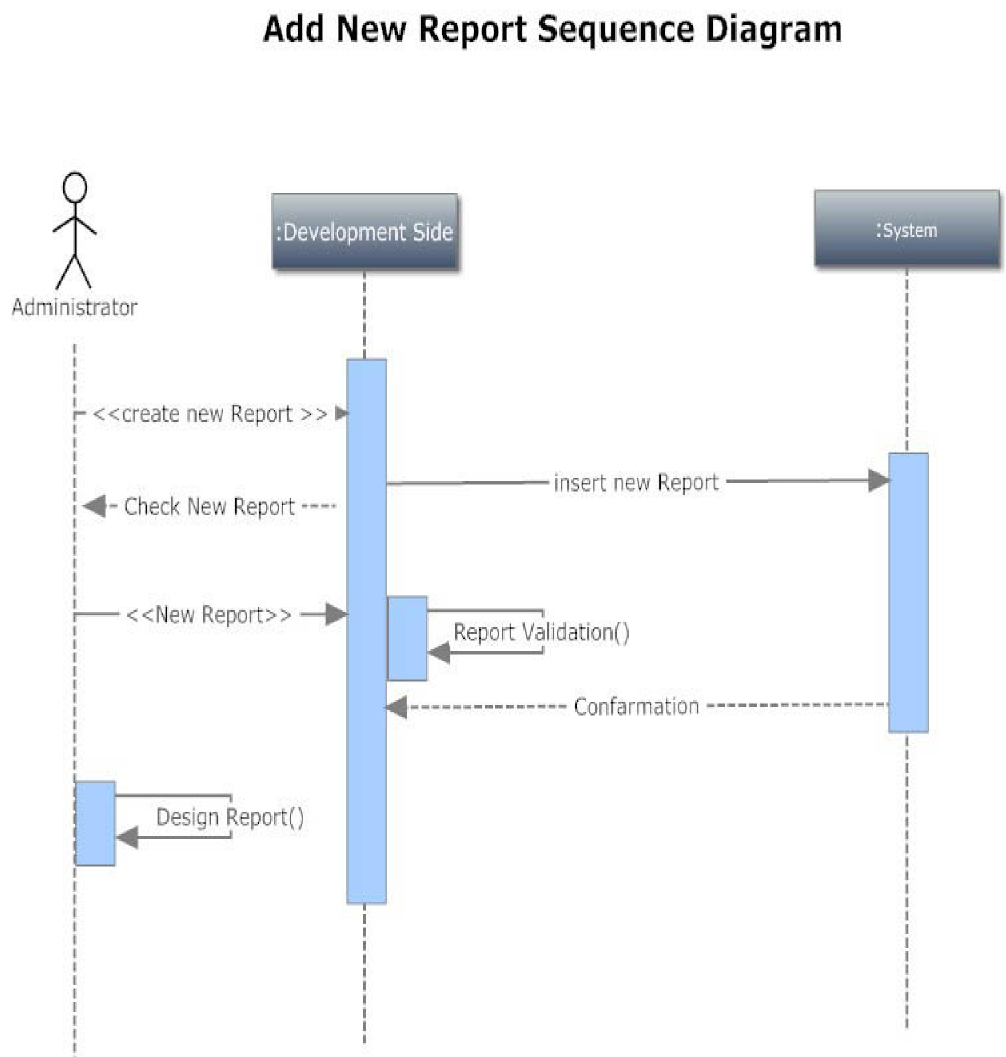
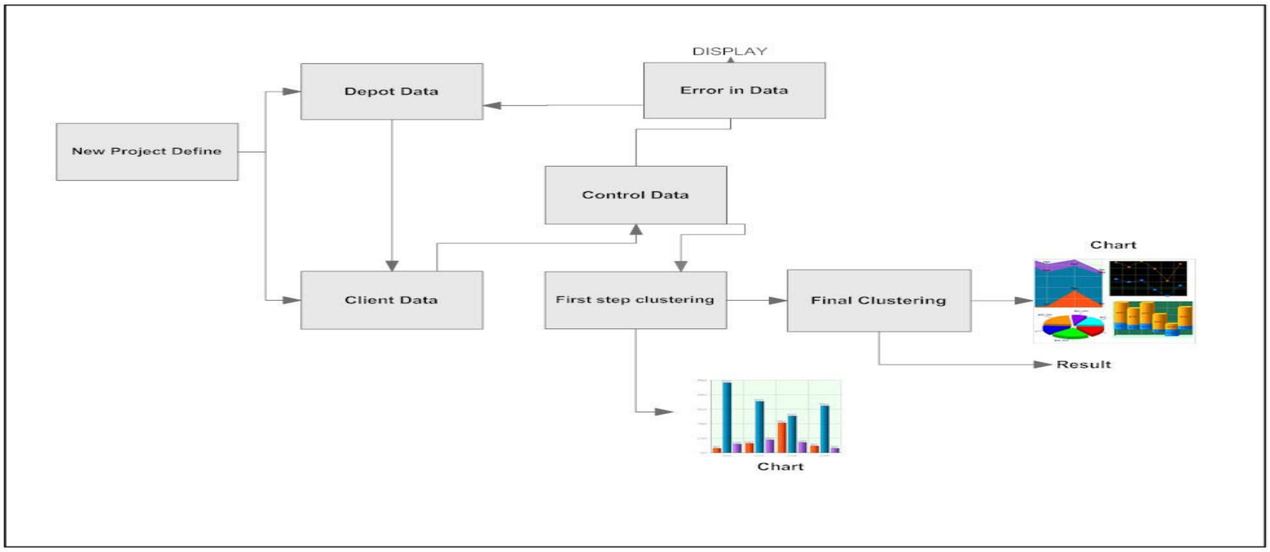



**Figure 6.11 :Add report sequence diagram**

## 6.8 Database Design

The Database Design of the proposed DSS is explained by means of an Entity and Relationship Diagram (Figure 6.12).



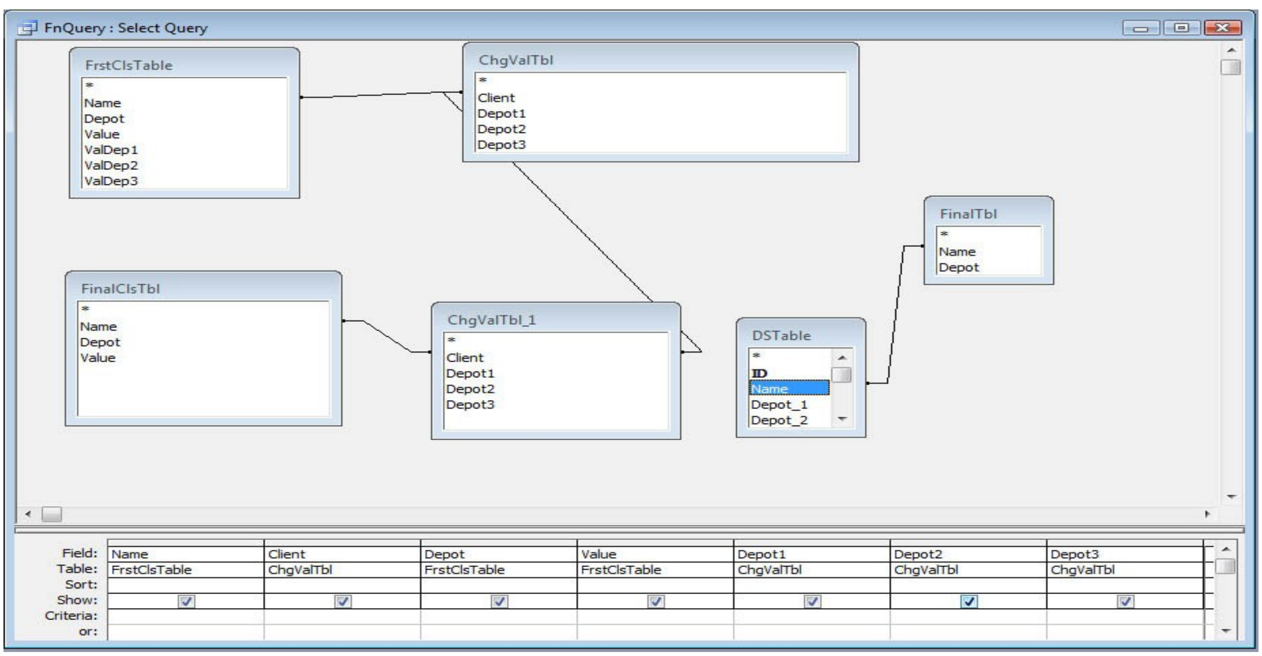




**Figure 6.12 :Entity and Relationship diagram**

## 6.9 Interfaces

### 6.9.1 User Interfaces

Users interact with the system using forms and buttons. Figure 6.13 presents the various forms associated with user interface of the proposed DSS.

User interface Login Screen:  This is for the Administrator to get into the software. It requires a user name and password.

**Project Details**: This shows the project status of various reports with their results.

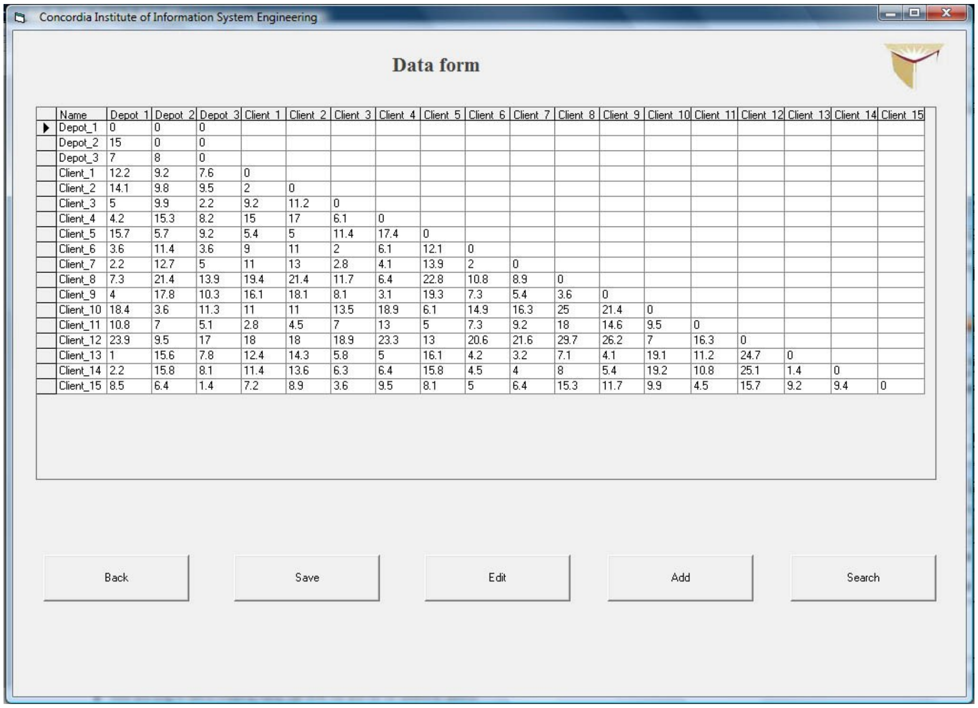
**New Registrations**: This utility is to create new project or clients in the system.

**Reports**: This utility is used to generate various reports of project in different steps of calculation.

**User Login** (Client Side): The user has to give a username and password by which he or she can access the software.

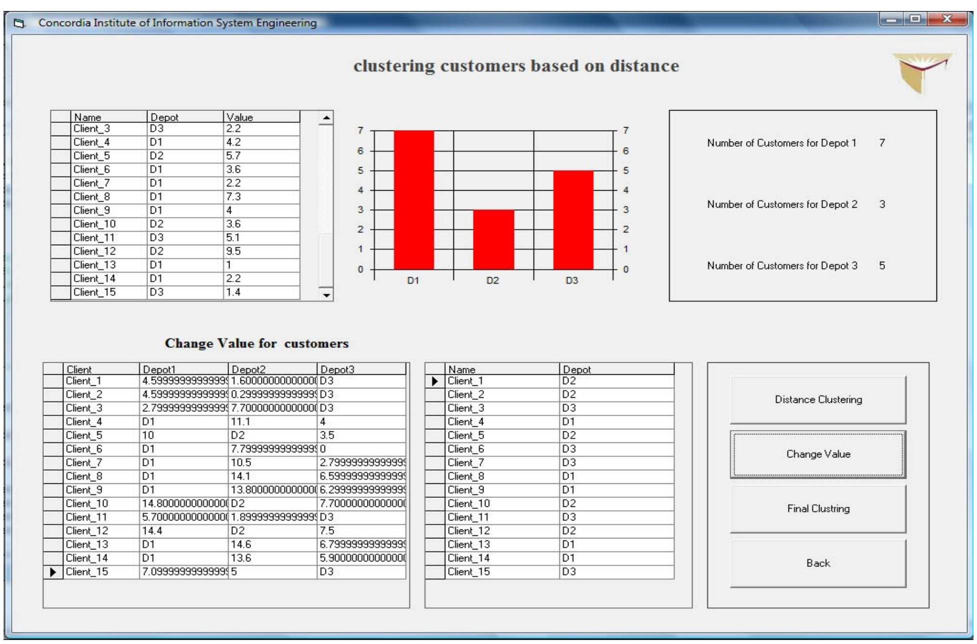
**Password Form**

## Data Form




| Name | Depot 1 | Depot 2 | Depot 3 | Client 1 | Client 2 | Client 3 | Client 4 | Client 5 | Client 6 | Client 7 | Client 8 | Client 9 | Client 10 | Client 11 | Client 12 | Client 13 | Client 14 | Client 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Depot_1 | 0 | 0 | 0 | | | | | | | | | | | | | | | |
| Depot_2 | 15 | 0 | 0 | | | | | | | | | | | | | | | |
| Depot_3 | 7 | 8 | 0 | | | | | | | | | | | | | | | |
| Client_1 | 12.2 | 9.2 | 7.6 | 0 | | | | | | | | | | | | | | |
| Client_2 | 14.1 | 9.8 | 9.5 | 2 | 0 | | | | | | | | | | | | | |
| Client_3 | 5 | 9.9 | 2.2 | 9.2 | 11.2 | 0 | | | | | | | | | | | | |
| Client_4 | 4.2 | 15.3 | 8.2 | 15 | 17 | 6.1 | 0 | | | | | | | | | | | |
| Client_5 | 15.7 | 5.7 | 9.2 | 5.4 | 5 | 11.4 | 17.4 | 0 | | | | | | | | | | |
| Client_6 | 3.6 | 11.4 | 3.6 | 9 | 11 | 2 | 6.1 | 12.1 | 0 | | | | | | | | | |
| Client_7 | 2.2 | 12.7 | 5 | 11 | 13 | 2.8 | 4.1 | 13.9 | 2 | 0 | | | | | | | | |
| Client_8 | 7.3 | 21.4 | 13.9 | 19.4 | 21.4 | 11.7 | 6.4 | 22.8 | 10.8 | 8.9 | 0 | | | | | | | |
| Client_9 | 4 | 17.8 | 10.3 | 16.1 | 18.1 | 8.1 | 3.1 | 19.3 | 7.3 | 5.4 | 3.6 | 0 | | | | | | |
| Client_10 | 18.4 | 3.6 | 11.3 | 11 | 11 | 13.5 | 18.9 | 6.1 | 14.9 | 16.3 | 25 | 21.4 | 0 | | | | | |
| Client_11 | 10.8 | 7 | 5.1 | 2.8 | 4.5 | 7 | 13 | 5 | 7.3 | 9.2 | 18 | 14.6 | 9.5 | 0 | | | | |
| Client_12 | 23.9 | 9.5 | 17 | 18 | 18 | 18.9 | 23.3 | 13 | 20.6 | 21.6 | 29.7 | 26.2 | 7 | 16.3 | 0 | | | |
| Client_13 | 1 | 15.6 | 7.8 | 12.4 | 14.3 | 5.8 | 5 | 16.1 | 4.2 | 3.2 | 7.1 | 4.1 | 19.1 | 11.2 | 24.7 | 0 | | |
| Client_14 | 2.2 | 15.8 | 8.1 | 11.4 | 13.6 | 6.3 | 6.4 | 15.8 | 4.5 | 4 | 8 | 5.4 | 19.2 | 10.8 | 25.1 | 1.4 | 0 | |
| Client_15 | 8.5 | 6.4 | 1.4 | 7.2 | 8.9 | 3.6 | 9.5 | 8.1 | 5 | 6.4 | 15.3 | 11.7 | 9.9 | 4.5 | 15.7 | 9.2 | 9.4 | 0 |

## Calculation Form

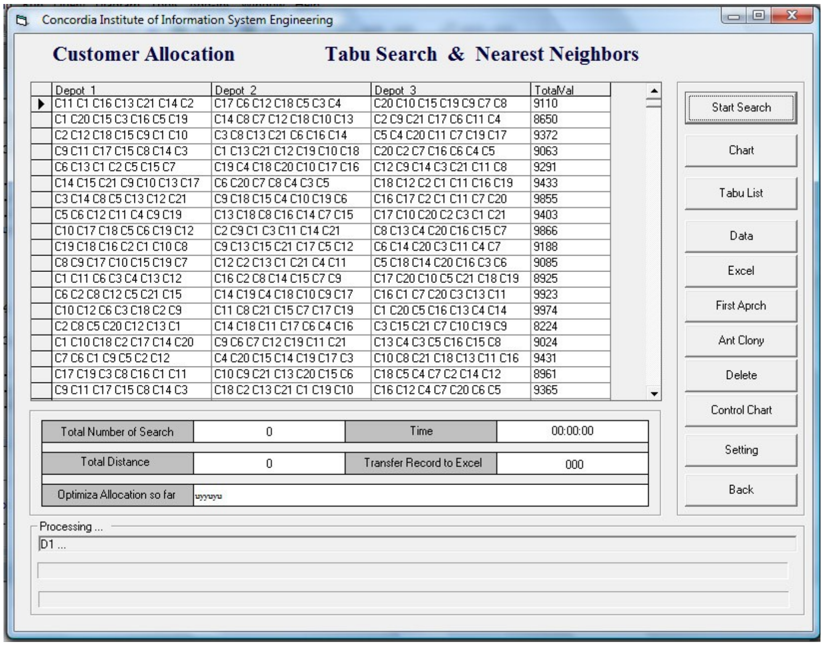



| Name | Depot | Value |
|---|---|---|
| Client_3 | D3 | 2.2 |
| Client_4 | D1 | 4.2 |
| Client_5 | D2 | 5.7 |
| Client_6 | D1 | 3.6 |
| Client_7 | D1 | 2.2 |
| Client_8 | D1 | 7.3 |
| Client_9 | D1 | 4 |
| Client_10 | D2 | 3.6 |
| Client_11 | D3 | 5.1 |
| Client_12 | D2 | 9.5 |
| Client_13 | D1 | 1 |
| Client_14 | D1 | 2.2 |
| Client_15 | D3 | 1.4 |

| Client | Depot1 | Depot2 | Depot3 |
|---|---|---|---|
| Client_1 | 4.59999999999999 | 1.60000000000000 | D3 |
| Client_2 | 4.59999999999999 | 0.29999999999999 | D3 |
| Client_3 | 2.79999999999999 | 7.70000000000000 | D3 |
| Client_4 | D1 | 11.1 | 4 |
| Client_5 | 10 | D2 | 3.5 |
| Client_6 | D1 | 7.79999999999999 | 0 |
| Client_7 | D1 | 10.5 | 2.79999999999999 |
| Client_8 | D1 | 14.1 | 6.59999999999999 |
| Client_9 | D1 | 13.8000000000000 | 6.29999999999999 |
| Client_10 | 14.8000000000000 | D2 | 7.70000000000000 |
| Client_11 | 5.70000000000000 | 1.89999999999999 | D3 |
| Client_12 | 14.4 | D2 | 7.5 |
| Client_13 | D1 | 14.6 | 6.79999999999999 |
| Client_14 | D1 | 13.6 | 5.90000000000000 |
| Client_15 | 7.09999999999999 | 5 | D3 |

| Name | Depot |
|---|---|
| Client_1 | D2 |
| Client_2 | D2 |
| Client_3 | D3 |
| Client_4 | D1 |
| Client_5 | D2 |
| Client_6 | D3 |
| Client_7 | D3 |
| Client_8 | D1 |
| Client_9 | D1 |
| Client_10 | D2 |
| Client_11 | D3 |
| Client_12 | D2 |
| Client_13 | D1 |
| Client_14 | D1 |
| Client_15 | D3 |

## Scheduling form




## Chart Form

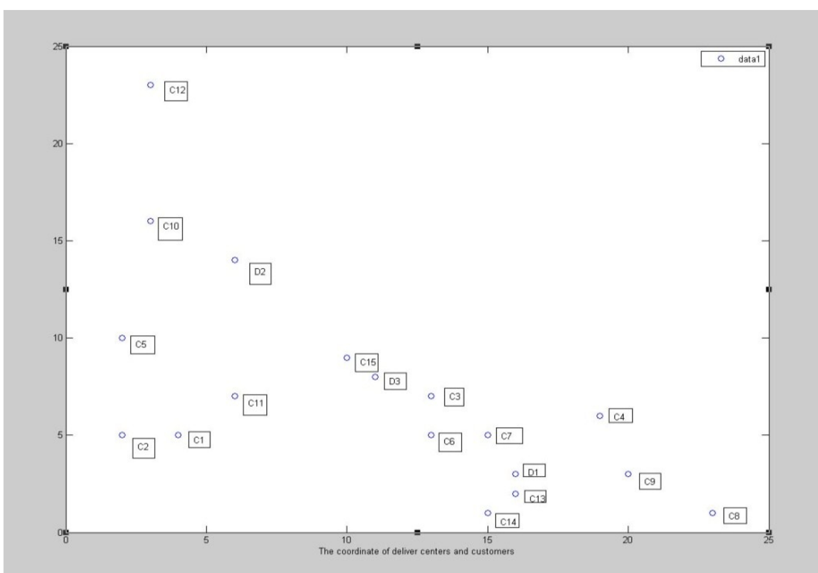



**Figure 6.13: User Interfaces**

### 6.9.2 Hardware Interfaces

The server is connected to the client systems. Also, the client has access to the database for accessing the project details. The client's access to the database in the server is read only.

### 6.9.3 Software Interfaces

Software interfaces is a multi-user, multi-tasking environment.

### 6.9.4 Communications Interfaces

Communication interfaces of the Goods Distribute System uses SQL Connection and Java Applets and hence requires HTTP for transmission of data or local LAN.

## 6.10 Testing Results

Software testing is any activity aimed at evaluating an attribute or capability of a program or system and determining that it meets its required results. Testing is more than just debugging. The purpose of testing can be quality assurance, verification and validation, or reliability estimation. Testing can be used as a generic metric as well, so in this project we have to test all the use cases of the system.

### 6.10.1 Software result

Based on the process method and the results of the software, we found the software method including clustering, scheduling and routing  for Distribute System Allocation and  the software is practical and could be executive (or executed?) in actual business activities or supply chain management. Besides, other critical factors for business play a key role in the efficiency of delivery process.

# Chapter 7:

# Conclusions and future works

## 7.1 Summary

Efficient distribution of goods is critical in maximizing revenues of logistics companies and minimizing environmental impacts on city residents and their environment. In this thesis, we address the problem of goods distribution planning in urban areas and propose a three step approach to address the following problems:

- Balanced allocation of customers to logistics depots
- Order scheduling of customers at logistics depots
- Vehicle allocation and route planning for goods distribution to customers

In the first step, we propose an integrated approach based on Nearest Neighbour and Tabu Search for balanced allocation of customers to logistics depots under congestion, access and timing regulations of the city. The objective is to minimize transportation costs subject to capacity constraints of logistics depots.

In the second step, we perform order scheduling for the customers allocated to each logistic depot using Genetic algorithms. The objective is to minimize distribution costs while respecting the time window constraints of customers, their order priorities, and any time or access regulation imposed by the municipal administration in the city.

In the third and the last step, we apply modified Dijkstra's algorithm to calculate fastest paths for goods delivery to customer considering the presence of congestion, road incident and road type. The proposed approaches are tested and validated by comparison against other standard approaches available in literature.

## 7.2 Advantages

Integrating the above three approaches, a prototype decision support system is developed for goods distribution planning in urban areas. The strength of the proposed work is its ability to deal with large size problem sets and generate fast, good quality solutions for goods distribution to customers. We also design and suggest better ways of efficiently distributing goods to cities, taking into consideration the city traffic condition, as well as access-timing-sizing regulations imposed by municipal administration in urban areas.

## 7.3 Limitations

The main limitation of our work is the lack of real time information on traffic conditions and vehicle availabilities during the planning process. Also, we have covered the last link of supply chain namely from depots (retailers) to clients, however, the ideas of the proposed work can be extended for application to other levels of supply chain networks.

## 7.4 Future Works

The next step of our work involves the following

- Managing immediate customer demands in routing and scheduling

- Congestion modelling
- Investigating the application of Intelligent Transportation Systems for data collection for efficient goods distribution planning
- Testing and validating the proposed goods distribution software for large problem instances.

# Chapter 8:

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