Performance Improvement Through Benchmarking for Small and Medium Manufacturers (SMM)

Von der Fakultät für Ingenieurwissenschaften, Abteilung Maschinenbau und Verfahrenstechnik der
Universität Duisburg-Essen
zur Erlangung des akademischen Grades
eines
Doktors der Ingenieurwissenschaften
Dr.-Ing.
genehmigte Dissertation

von

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Tag der mündlichen Prüfung: 08.11.2013

ABSTRACT

The main cost factors within a supply chain can be put into the categories of production, transportation, and inventory costs. The composition of these operational costs relative to total costs varies largely by industry. However, production cost is the largest of all in almost all the industries, followed by transportation and inventory costs. Optimizing one of these categories without consideration of the others may increase the total cost and reduce the overall performance.

This dissertation deals with the production distribution problem of developing synchronized strategies to improve the supply chain performance and to minimize the total cost. A real case study is investigated. This real-life case study is a powder detergent plant located in Libya.

There are two main scenarios evaluated. The first scenario is the conventional plan, where the manufacturer dominates. This means the manufacturer finds his own optimum job-scheduling plan, and the distributor tries to find the optimum plan according to it. This will increase the distribution cost. The second scenario involves synchronizing the production, inventory and transportation schedules.

A Java program and SimAl (job-scheduling software) were constructed for modelling conventional and integrated scenarios. The two scenarios were compared and validated. The case study considered multiple products and a flowshop system which is difficult to schedule. The results show that the total costs, including setup, inventory and transportation, can be minimized when the synchronized system is applied.

Abstrakt

Die wichtigsten Kostenfaktoren innerhalb einer Lieferkette lassen sich drei Kategorien zuordnen: Produktions-, Transport-und Lagerkosten. Die Strukturen dieser operativen Kosten im Hinblick auf die Gesamtkosten variieren stark je nach Industriesektor. Produktionskosten stellen dennoch die höchste Kostenart in fast allen Branchen dar, weniger bedeutend folgen danach jeweils die Transport- und Lagerkosten. Die Optimierung einer dieser Kategorien ohne Rücksicht auf die anderen kann zur Erhöhung der Gesamtkosten sowie der allgemeinen Leistungsfähigkeit führen.

Diese Dissertation befasst sich mit dem „production distribution problem“ wobei synchronisierte Strategien entwickelt werden können, um die Leistung der Supply Chain zu verbessern und gleichzeitig die Gesamtkosten zu minimieren. Dazu wurde eine Fallstudie aus der Realität untersucht, nämlich das Praxisbeispiel eines Herstellers von Waschmitteln.

Zwei Hauptszenarien werden bewertet. Das erste Szenario ist der konventionelle Plan, wobei die Hersteller dominieren. Dies bedeutet, dass der Hersteller findet seinen eigenen optimalen Job-Scheduling-Plan, während die Distribution versucht mit Hilfe dessen ihren optimalen Plan zu finden. Dadurch erhöhen sich die Distributionskosten. Das zweite Szenario betrifft die Synchronisation der Produktions-, Lagerhaltungs- und Transportzeitpläne.

Ein zu diesem Zweck entwickeltes Java-Programm und die Job-Scheduling-Software Simal wurden für die Modellierung der konventionellen und integrierten Szenarien verwendet. Beide Szenarien wurden verglichen und validiert. Die Fallstudie betrachtet mehrere Produkte sowie ein schwer zu planendes flowshop- System. Die Ergebnisse zeigen, dass die Gesamtkosten, einschließlich der Einrichtungs-, Lager- und Transportkosten, minimiert werden können, wenn das synchronisierte System angewendet wird.

Dedication

TO

My mother, and My father

My wife, and My daughters

My brothers and my sisters

Ibrahim Ahmed Badi

Acknowledgments

I wish to express my sincere gratitude to my supervisor, Prof. Dr.-Bernd Noche, for the many inspirational discussions and guidance offered throughout this work.

Special thanks to all academic and technical staff of Transportsysteme und – Logistik Institute for their many helpful suggestions and technical support.

I wish to acknowledge my gratitude to the team work of Misurata detergent factory, especially to Eng. Abdulhadi Elgaied, Eng. Abdulmajid Abusitta and Eng. Imad Elshwin for all information required.

Also, I would like to thank the team work of Industrial Information Center, Misurata, especially Mr. Abdulkarim Hwidi.

I also owe special gratitude to my wife, from whom I always get support and lovely care, especially during my study in Germany.

Last but not least, I would like to thank my family (mother, father, brothers, and sisters) for their support right from the very beginning of my study.

Duisburg, 2013

Ibrahim Ahmed Badi

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Abbreviations

1-M-M	One Plant Multi-depot Multi-retailer
DC	Distribution Center
EDD	Earliest Due date
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
FIFO	First In First Out
FS	Flowshop Scheduling
FSP	Flowshop Scheduling Problem
IRP	Inventory Routing Problem
LAP	Location Allocation Problem
LC	Load Consolidation
LPT	Largest Processing Time
LRP	Location Routing Problem
LTL	Less-than Truck Load
MDLRP	Multi Depot Location Routing Problem
M-M	Multi-depot Multi-retailer
NEH	Nawaz, Enscore, Ham algorithm
PDA	Production Data Acquisition
PFSP	Permutation Flowshop Scheduling Problem
PIDRP	Production Inventory Distribution Routing Problem
Prmu	Permutation flowshop
SSL	Service Sequence List
TSP	Traveling Salesman Problem
VMI	Vendor Managed Inventory
VRP	Vehicle Routing Problem

1. Introduction

Nowadays supply chain, which is an extension definition of logistics, has become more and more important in our daily life due to the rapid development of society. Quick delivery and potential cost benefit are required, both for transport and for all economic-related events. Since logistics played a dominant role in the Second World War, more attention to logistics was inevitable.

The management of the entire supply chain has become possible in recent years due to new developments in the technology of information systems. However, it is still obviously much more difficult than dealing with each of the traditional problems of production, transportation and inventory decisions separately.

Supply chain research now can be divided according to two directions. One direction is submitting the new methods to not only cater to the needs of the more complex supply chain system but also to guide the second direction. For example, vendor-managed inventory (VMI) relative to the customer-managed inventory (CMI) and ship-to-stock (STS) purchasing concept is employed in the industry field now: the method which integrated the production and transportation problem relative to the independent research in production management, inventory management and distribution management before. The second direction is grounded on the basic method in the first direction, aiming at the different and detailed case study in practice to probe as deeply as possible to find out better methods and solutions in order to adapt the individual company situation.

Several examples can be found in the literature proving that models coordinating at least two stages of the supply chain can detect new opportunities for improving the efficiency of the supply chain.[74] Various types of coordination in a supply chain have been researched in the literature.

The supply chain of a typical product starts with material input, followed by production, and finally distribution of the end product to customers. The cost of a product includes not only the cost of factory resources to convert materials to a finished item but also the cost of resources to make a sale, deliver the product to customers, and service the customers. According to that, firms have to organize all the activities in the supply chain.[91]

The composition of production, transportation and inventory costs, relative to total costs, varies largely by industry; however, production costs are the largest of all, in almost all the industries, followed by transportation and inventory costs.

Production and distribution scheduling decisions are typically made independently of each other, which means organizations focus their efforts on making effective decisions within the facility. The cooperation between decisions made at different stages of the supply chain is the central issue in the supply chain management; the decision makers at each stage have different objectives. For example, the manufacturer aims to minimize total production costs, and match the customer's due dates. The manufacturer prefers to produce individual products in large batch sizes, which can minimize the setup costs. The distributor aims to minimize the inventory costs and transportation costs. The overall system performance will be poor, in many cases, if each decision maker, at each different stage, uses its optimal schedule. It is well recognized that there is a greater opportunity for cost saving in managing supply chain coordination than in improving individual function areas.[88] Therefore, the coordination problem is to find a schedule for each stage that will provide a better overall system performance.

1.1 Background

Most companies nowadays are organized into networks of manufacturing and distribution sites that procure raw materials, process them into finished goods, and distribute the finished goods to customers. The goal is to deliver the right product at the right time to the right place for the right price.

For many years, companies and researchers failed to take an integrated view of the entire supply chain. They considered only one piece of the overall problem, such as production or distribution sub-models. These sub-models were optimized separately and the solutions were then joined together to establish operating policies.

The system of supply chain involves many units, such as supplier, transporter, production plants, warehouse and customers. All parties directly or indirectly fulfill customers' requests. Initially, those units are considered as independent; therefore, the problems concerning different units are modelled separately. An optimal solution is desired. As many new algorithms and approaches have been proposed in the supply chain system and computer science has been rapidly developed, solving complex problems with an integrated approach has become possible. The main current issue is how to integrate the units – supplier, transporter, production plants, warehouses, and customers – in a systematic manner.

The production-distribution problem usually consists of a factory, which manufactures products, and a set of warehouses that stock these products ready to deliver them to retailers' stores where the demand for these products is generated. The manufacture of a final product requires several different production processes. Each process is assumed to take place at a given production stage. The final product, delivered to one of the warehouses, and then to the retailers, must satisfy customer requirements.

The supply chain stages can be decoupled if there is a sufficient amount of inventory between them. The complexity of the decision making, in this way, is reduced because each stage is treated separately. However, ignoring stages dependencies can have costly consequences. Moving towards coordination can minimize the total cost while continuously improving the customer service level. Figure (1.1) shows the three stages of the supply chain.

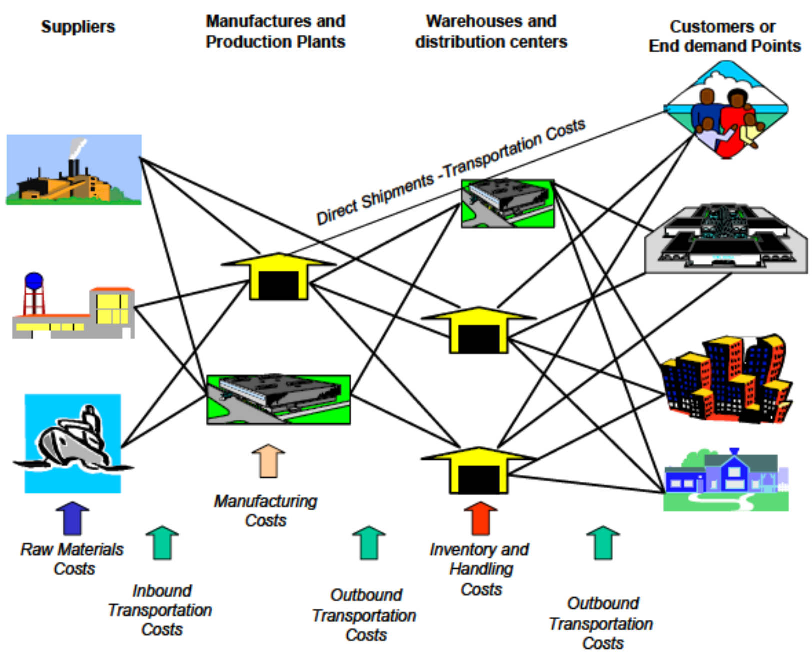


Figure 1.1: The traditional three stages of the supply chain.[94]

Managing production and distribution problems separately, as mentioned above, leads to increasing inventory levels, which leads to increased holding costs and longer lead times of the products through the supply chain.

The primary difference between analyzing a supply chain and analyzing a production system or a distribution system is that in a supply chain, we may have to simultaneously consider different and sometimes conflicting objectives from different participants, or different departments within the same participant. For example, minimizing production costs at the production line means minimizing the number of batches. Similarly, optimizing the distribution costs to a supplier by sending large shipments may determine an increase in the inventory holding costs at the warehouse.

The production-distribution link in the supply chain can take on many forms. Products can be manufactured and sent to distribution centers, retailers or plants. The literature addressing both production planning and distribution planning is extensive; however, there are few models that attempt to address these problems simultaneously. There are several reasons why this may be true. Firstly, many problems in these areas are tremendously hard to solve by themselves, with both vehicle routing and machine scheduling falling into this category. Secondly, in practice, these problems are often separated by inventory buffers, and finally, different departments are often responsible for these two planning activities.

In general, the plant may involve one machine, or many machines, to produce different products, and the machine sequence may be in parallel or series sequences. Usually, there will be a setup time when changing from one product to another.

The flow shop scheduling with setup time is considered in this study. Production scheduling, which is a part of the planning and control of individual production units, lies at the heart of the performance of manufacturing organizations. The need for efficient scheduling has increased in the last decades because of needs to fulfill customer requirements. However, although scheduling research activities have moved from purely academic exercises to serious attempts to solve real-word problems. Flowshop Scheduling is used to determine the optimal sequence of n jobs to be processed on m machines in the same order. Permutation Flowshop Scheduling Problems (PFSP) require same job sequence on all the machines with the constraint that machines can only process one job at a time and jobs can be processed by only one machine at a time. No machine is allowed to remain idle when a job is ready for processing. Such problems are NP hard and hence optimal solutions are not guaranteed but heuristics have been shown to produce good working solutions. Scheduling is an important aspect of operational level floor decisions. Makespan (maximum completion time) and maximum tardiness are among the most commonly used criteria in the flow shop scheduling research. Makespan is a measure of system utilization while maximum tardiness is a measure of performance in meeting customer due dates.

In the case of a manufacturer that produces more than one product, a schedule that produces each product in lot sizes is preferred in order to minimize the total setup costs. However, the distributor prefers a schedule where batches of the products will be shipped together. In this case, the distributor can minimize its distribution costs.

Figure (1.2) shows a case where the production and transportation schedules are independent.

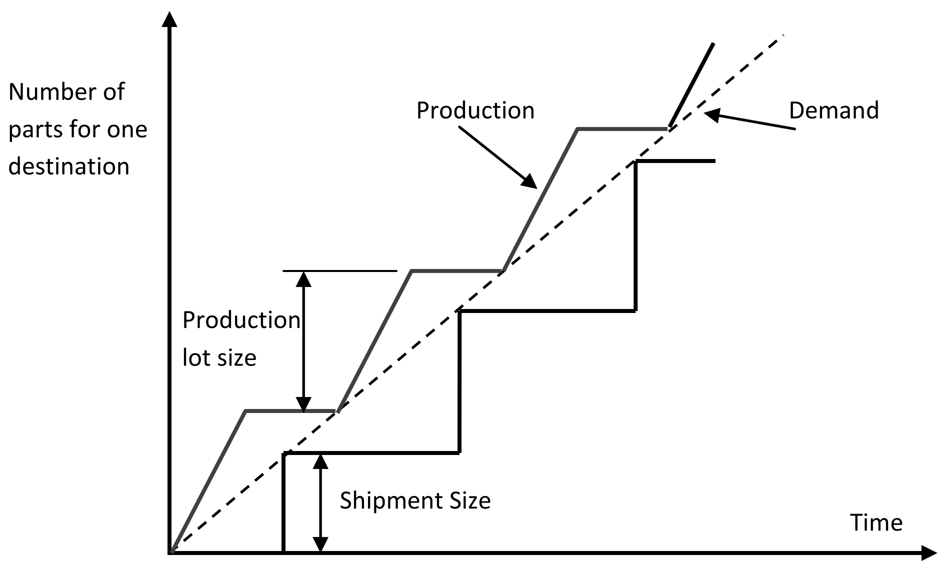


Figure (1.2): Cumulative production and departures for independent schedules.[17]

As shown in the figure, the flat line occurs while other products are produced for other destinations. The production lot size is the quantity produced for this destination.

In this example of an independent schedule, the shipment size is calculated independently of the production lot size. The horizontal distance represents the time that a product consumes in inventory.

Figure (1.3) shows the costs incurred in this case [17].

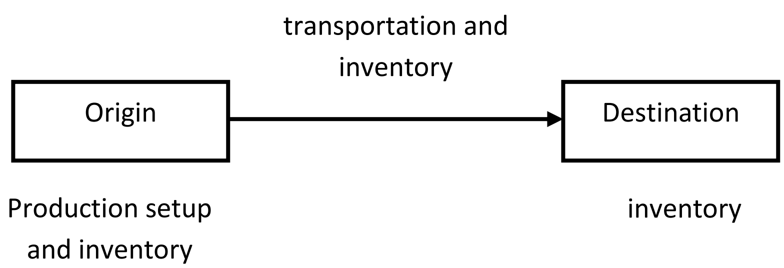


Figure (1.3): Costs on one link of the network[17].

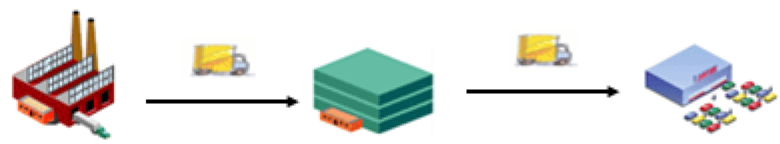
1.2. Overview of the research problem

Companies deliver products to their customers using a logistics distribution network. Such networks typically consist of product flows from the producers to the customers through distribution centres (warehouses) and retailers. Companies generally need to make decisions on production planning, inventory levels and transportation in each level of the logistics distribution network in such a way that customer demand is satisfied at minimum cost.

In this thesis, the possibility of moving from the singular decision-making processes toward a more coordinated and integrated system is studied. The system suggested consists of a single production facility which produces multiple products, and multiple warehouses and retailers, as shown in Figure 1.4.

Achieving a level of integration that will yield new benefits requires that the production and distribution decisions be made to balance setup, holding and delivery costs.

In the model suggested, excess production can be stored at either the plant, depots or retailers, up to a limit, to fulfill the customers' requirements. It is assumed that daily demand is known for all retailers. Deliveries are made using homogenous vehicles.



The plant has different stages, and produce multi products. There is a setup cost between different products at different stages.

Figure (1.4): Block diagram of the system considered

The manufacturer produces different products, which are processed through different machines, and those products are delivered to retailers through warehouses.

There are setup times (and costs) when changes occur between these products. The objective of the plant is to find a plan which can minimize the total setup costs.

Also, there are different warehouses that receive these products and deliver them to retailers demanding them. The objective of the warehouses and retailers is to minimize the inventory and transportation costs.

Obviously, there is a conflict between these objectives; the plant prefers to manufacture in batch production, while the retailers prefer to receive just their orders, and on time.

Inventory and transportation policies are intertwined. When distributing a product, three main strategies can be used: direct shipment, warehousing and cross-docking. If a direct shipment strategy is used, goods are shipped directly from the manufacturer to the end-user (the retailers in the case of retail goods) (see Figure 1.5a). Direct shipments eliminate the expenses of operating a DC and reduce lead times. On the other hand, if a typical customer shipment size is small and customers are dispersed over a wide geographic area, a large fleet of small trucks may be required. As a result, direct shipment is common when fully loaded trucks are required by customers or when perishable goods have to be delivered promptly. Warehousing is a traditional approach in which goods are received by warehouses and stored in tanks, pallet racks or on shelves (see Figure 1.5b). When an order arrives, items are retrieved, packed and shipped to the customer. Warehousing consists of four major functions: reception of the incoming goods, storage, order picking and shipping. Out of these four functions, storage and order picking are the most expensive because of inventory holding costs and labour costs, respectively. Cross-docking (also referred to as just-in-time distribution) is a relatively new logistics technique that has been successfully applied by several retail chains (see Figure 1.5c). A cross-dock is a trans-shipment facility in which incoming shipments (possibly originating from several manufacturers) are sorted, consolidated with other products and transferred directly to outgoing trailers without intermediate storage or order picking. As a result, shipments spend just a few hours at the facility. In pre-distribution cross-docking, goods are assigned to a retail outlet before the shipment leaves the vendor. In post-distribution cross-docking, the cross-dock itself allocates goods to the retail outlets. In order to work properly, cross-docking requires high volumes and low variability of demand (otherwise it is difficult to match supply and demand), as well as easy-to-handle products. Moreover, a suitable information system is needed to coordinate inbound and outbound flows. [34]

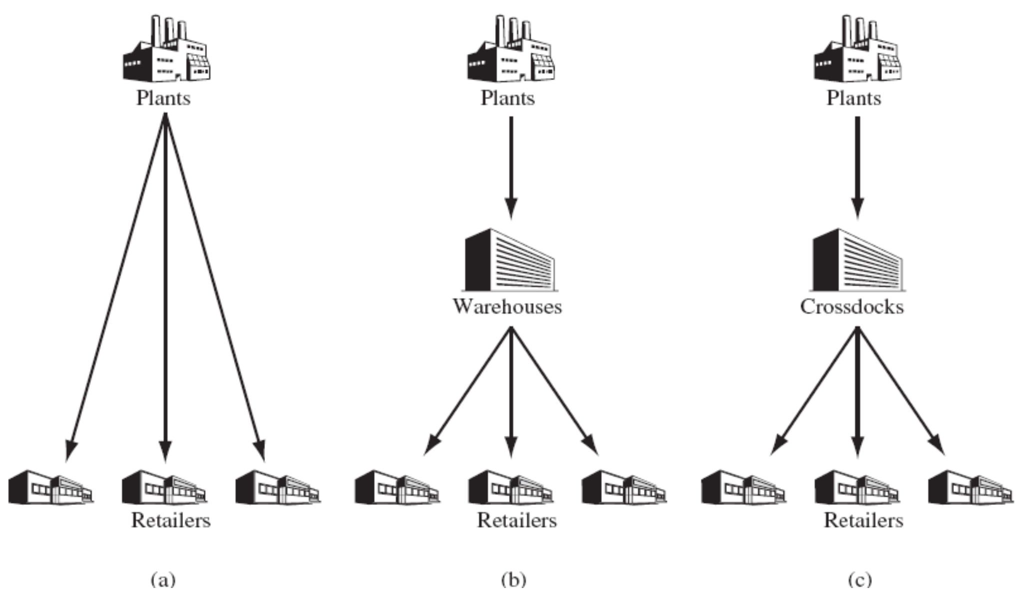


Figure 1.5 Inventory and Transportation Strategies[34]

If a warehousing strategy is used, one has to decide whether to select a centralized or a decentralized system. In centralized warehousing, a single warehouse serves the whole market, while in decentralized warehousing the market is divided into different zones, each of which is served by a different (smaller) warehouse. Decentralized warehousing leads to reduced lead times since the warehouses are much closer to the customers. On the other hand, centralized warehousing is characterized by lower facility costs because of larger economies of scale. In addition, if customers' demands are uncorrelated, the aggregate safety stock required by a centralized system is significantly smaller than the sum of the safety stocks in a decentralized system. This phenomenon (known as risk pooling) can be explained qualitatively as follows: under the above hypotheses, if the demand from a customer zone is higher than the average, then there will probably be a customer zone whose demand is below average. Hence, demand originally allocated to a zone can be reallocated to the other and, as a result, lower safety stocks are required. Finally, inbound transportation costs (the costs of shipping the goods from manufacturing plants to warehouses) are lower in a centralized system, while outbound transportation costs (the costs of delivering the goods from the warehouses to the customers) are lower in a decentralized system. [34]

1.3 Research motivation and objectives

This thesis was motivated by a real-life powder detergent company located in Libya. The company wanted to optimize its supply chain network and distribution strategies.

The supply chain distribution network model that should be analysed is typically complex. The mathematical optimization techniques have some limitations as they deal only with static models; however, simulation-based tools, which take into account the dynamics of the system, are capable of characterizing system performance for a given design.

Comparisons between different scenarios will be made. Figure 1.6 shows the different scenarios suggested.

There are two different scenarios: the first one is where the plant dominates; in this scenario the plant will calculate its optimum plan, which will minimize the production (setup) costs. According to the plant plan, the different products will be delivered to different warehouses and then to the retailers. The second scenario is to make an optimum plan, for the whole supply chain, to minimize the total costs.

This thesis focuses on a manufacturing system, which produces multiple products. Setup times are incurred when changes need to be made between manufacturing these products. The final products will be delivered to the retailers according to their orders.

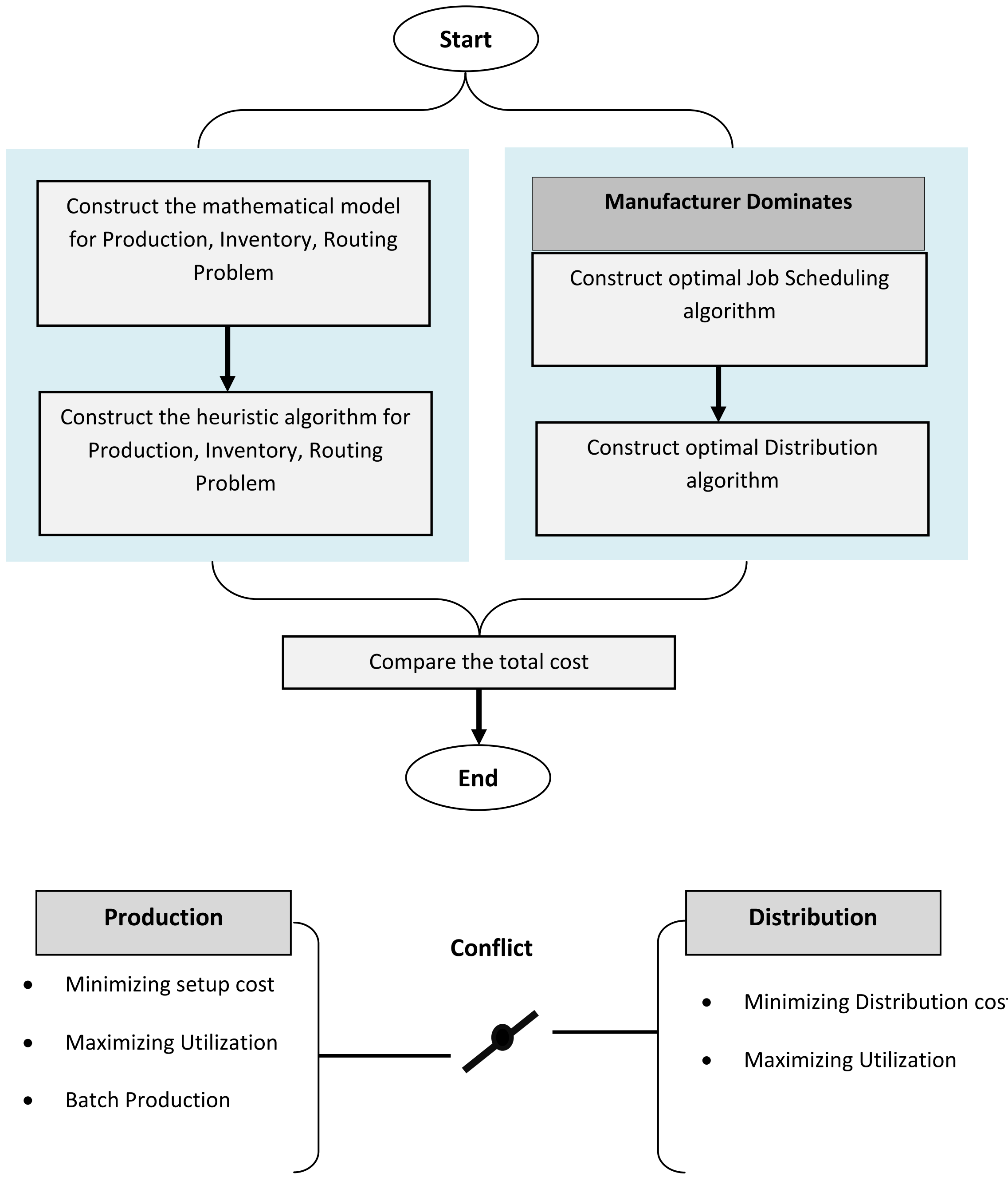


Figure (1.6): Suggested scenarios to solve the problem

The main objectives of this thesis are:

- To minimize the total system costs by simultaneously considering the production-distribution decisions.

- To develop new tools and practices that would allow the plant to design a more effective schedule.
- To answer questions; e.g., how much should the company produce from each product, when should they produce them, how much should be kept in the inventory, and which route should they followed?

1.4 Problem Description

The problem considered in this thesis involves one plant, which produces different products through a flow shop production line. A setup time is incurred whenever changes between productions occur.

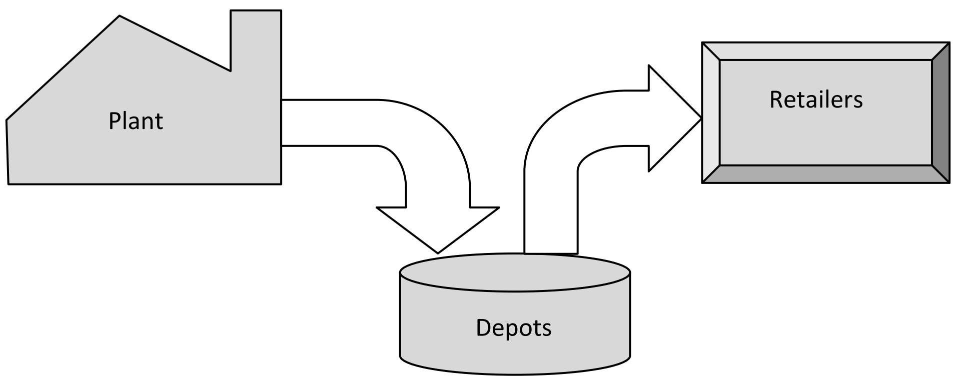


Figure (1.7): General description of the problem

The plant aims to minimize the setup costs. There are retailers who have deterministic orders and a limited inventory capacity with known holding costs. The retailers' aim is to minimize the total holding costs; however, the distributor also aims to minimize their distribution costs. The products are shipped in cartons, and the trucks have limited capacity with variable costs related to the total distance travelled. The total costs considered consist of the setup costs, distribution costs, and inventory costs.

1.5 Thesis overview

This thesis is structured as follows: chapter 2 presents the literature review on the flow shop scheduling problem, and the integrated production routing and inventory problem. The scenario of the manufacturer is explained in chapter 3; where the mathematical model of the problem is explained (the NEHT[61] (Nawaz , Enscore, Ham) algorithm is used to solve the problem). According to the solution obtained, the distribution costs are calculated using VMI model, with product and customer improvements. Chapter 4 represents the synchronized production-routing-inventory problem. The mathematical model is developed, and a heuristic algorithm is suggested. Chapter 5 deals with location routing problems, the aim being to suggest a new location for the depots in order to minimize the total costs (the models used here are ADD-DROP algorithms). The case study represented in Chapter 6 explains the production stages at the plant and also gives a general overview of the detergent powder industry. Chapter 7 includes the calculations and results of the different models and scenarios. Conclusions are represented in chapter 8.

2. Literature Review

Shuguang Liu [97] classified the literature review on the production inventory distribution problem as shown in Figure 2.1.

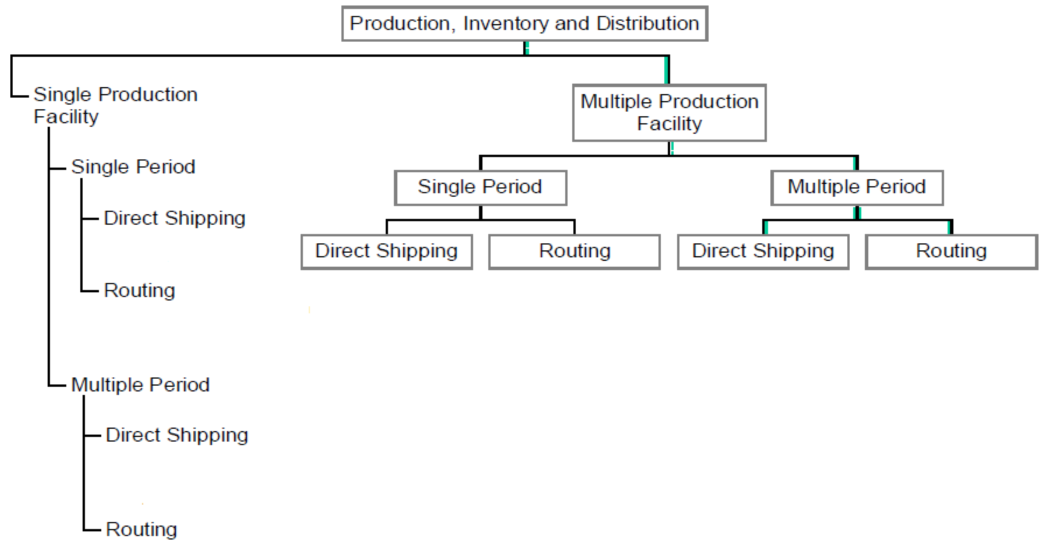


Figure 2.1 Classification of literature on PIDRP [97]

He aims to minimize the total production, inventory and delivery costs.

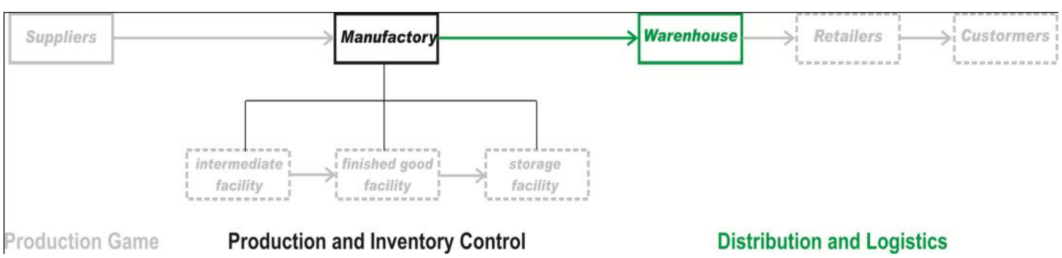


Figure 2.2: The production, inventory and distribution problem

A single product and a set of plants: each has its own production capacity, inventory capacity, raw material supply contract, inventory holding cost, and production cost to be considered. Associated with each plant is a heterogeneous fleet of transporters. A set of customer demand centres (DCs) is located over a wide geographical region; each is assigned its own demand per time period in the planning horizon, its own inventory capacity, holding cost, and safety stock requirement. The problem is to determine the operation schedules to coordinate the production, inventory, and transportation routing operations while the resulting operation cost (i.e., the sum of production, inventory and transportation cost) over a given planning horizon is minimized.

A two-phase methodology is proposed. In phase I, Liu solves a restricted coordination problem which keeps all the constraints in P except that the transporter routings are limited to direct shipment. He proves that the resulting optimal solution to the Phase I problem is always feasible to P, thus giving an upper bound solution to P. He determines the optimal number of trips (per time period) performed by each individual transporter, in terms of its very own capacity, cost and speed. In phase II, he proposes a heuristic transporter routing algorithm, the Load Consolidation (LC) algorithm, that removes all the less-than-truck-load (LTL) assignments from the phase I solution and consolidates such assignments into transporter routing schedules subject to transporter capacity and available time constraints.

Ivan Ferretti et al.[42] present the algorithmic solution, based on an Ant System metaheuristic, of an industrial production-inventory problem in a steel continuous-casting plant. The model proposes aims to find the most profitable production schedule of the steel billets.

Figure 2.3 shows the analyzed unit relative to the whole supply chain in this study.

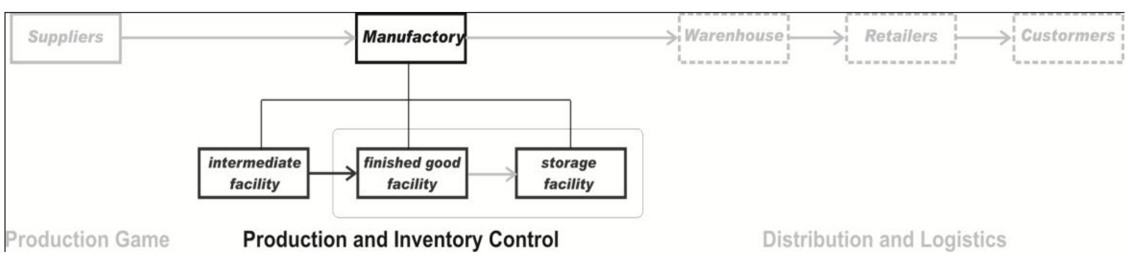


Figure 2.3: Production and Inventory Scheduling in Supply Chain

The paper focuses on the optimization of the production schedule in a steel plant. The final result of the algorithm is the sequence of customer orders to be produced, thus defining the starting date of each job and considering the delivery date required by the customer. If a delay in the delivery is to be introduced, the objective function accounts it as a penalty cost.

The Ant System which used to solve the problem is derived from the Travelling Salesman Problem (TSP) Ant System. The TSP Ant System finds the shortest path that links each node. The Billet Ant System searches a production sequence that maximizes the profit.

Renato De Matta and Tan Miller[85] studied the problem of coordinating the short-term production and inter-facility transportation scheduling decisions between a plant that produces intermediate products and a finishing plant which processes the intermediate products into finished goods; Figure 2.4 shows the problem.

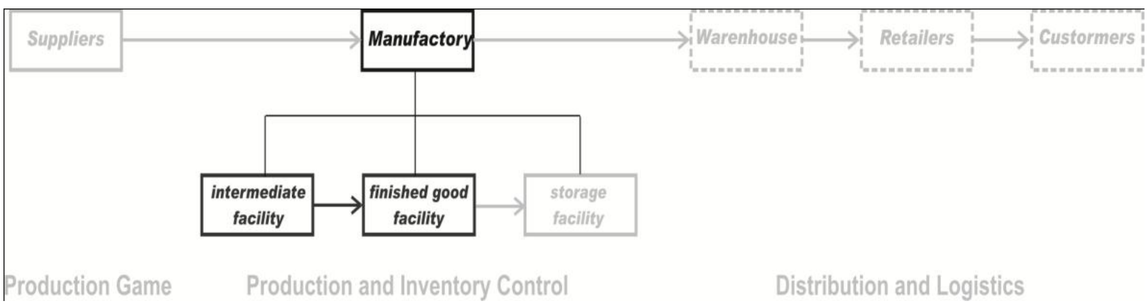


Figure 2.4: Production and inter-facility transportation scheduling

The goal is to develop a better understanding of the general relationships between production and transportation scheduling decisions – in particular, how changes in plant capacity and costs affect the coordination of scheduling decisions, as well as the choice of transportation modes and carriers. They formulate the problem as a mixed-integer programming model.

Because of the large number of integer variables for even a small problem, obtaining integer solutions for (P) via a branch-and-bound procedure requires evaluating a large number of branches and performing a large number of simplex pivots. They modified the process for the problem in order to solve directly by branch-and-bound.

Zhi-Long Chen[112] considered the supply chain of a manufacturer who produces time-sensitive products that have a large variety, a short lifecycle, and are sold in a very short selling season.

The coordination is the production and distribution unit, as shown in Figure 2.5.

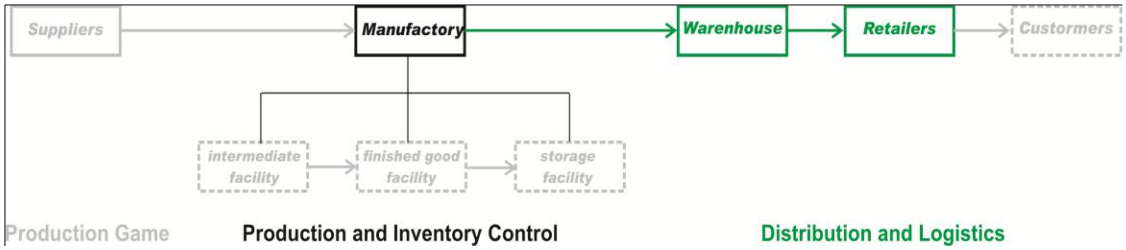


Figure 2.5: Order assignment and scheduling

The supply chain consists of multiple overseas plants and a domestic distribution centre (DC), as shown in Figure (2.6). Retail orders are first processed at the plants and then shipped from the plants to the DC for distribution to domestic retailers. Due to variations in productivity and labour costs at different plants, the processing time and cost of an order are dependent on the plant to which it is assigned.

The model tries to find which orders are to be assigned to which plants, how to schedule the production of the assigned orders at each plant, and how to schedule the distribution of the completed orders from each plant to the distribution centre.

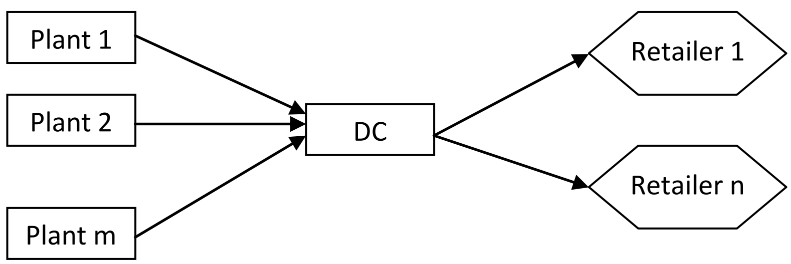


Figure 2.6: Problem description for order assignment and scheduling

Dennis E. Blumenfeld[17] determined optimal shipping strategies by analyzing trade-offs between transportation, inventory and production set-up costs on freight networks.

Conditions are identified so that networks involving direct shipments between many origins and destinations can be analyzed on a link-by-link basis.

He simultaneously determines optimal routes and shipment sizes for networks with a consolidation terminal and concave cost functions.

The standard economic order quantity (EOQ) methods are used to solve the direct shipment problem. For the shipping via consolidation terminal problem, optimal shipment sizes can be determined for each link independently, as in direct shipping. The total cost can be minimized by minimizing the cost on each link separately. For solving the mixed strategy network, Blumenfeld decomposes the network into several sub-networks based on the “all or nothing” principle.

Consider a network of two origins and many destinations. There are only two inbound links. In general, for S shipment sizes and M origins, the number of combinations is SM. The optimal shipment sizes can be determined for each link independently, using the EOQ formula.

M. Zandieh and Zavaradehi[75] studied the problem of synchronized scheduling of single machine and air transportation in supply chain management.

The overall problem is decomposed into two sub-problems, consisting of the air transportation allocation problem and a single machine scheduling problem, which they considered together. The detail structures are shown in Figure 2.7.

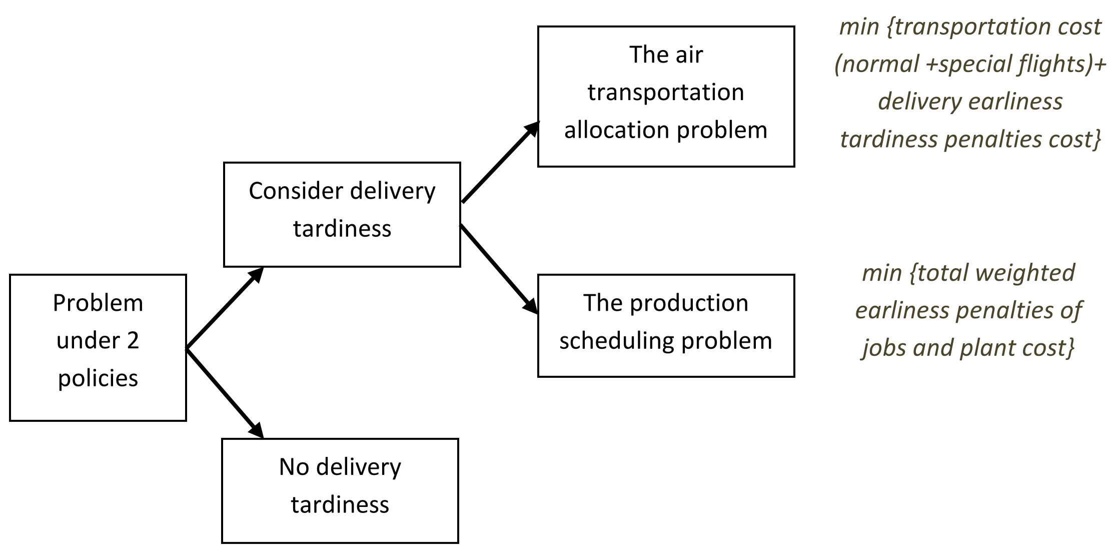


Figure 2.7: Problem description

Kadir Ertogral et al.[48] investigated the effects of integrating production and transportation planning. The integrated optimization models that reconcile the viewpoints from transportation and production planning and analyze the costs introduced by coordination are presented.

Based on MLMILP (Multi-level multi-item dynamic-capacitated lot-sizing problem) and m-PDPTW (multi-vehicle pickup and delivery problem with time windows), they explain and solve the production-planning model and transportation-planning model separately. Then, according to the connected variables, the linkages between these two models are analyzed in order to get the solution.

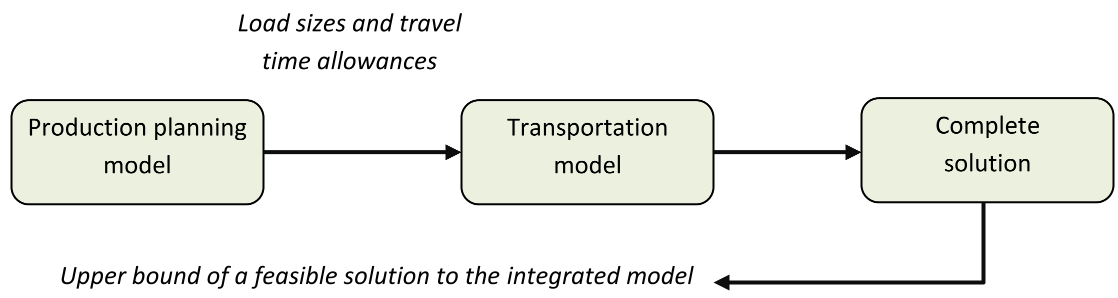


Figure 2.8: Problem formulation

The Lagrangean decomposition method is used to solve the integrating production and transportation planning. First, the problem is decomposed into production sub-problem and transportation sub-problem, both with coupling constraints. Then the solution process is shown in Figure 2.9.

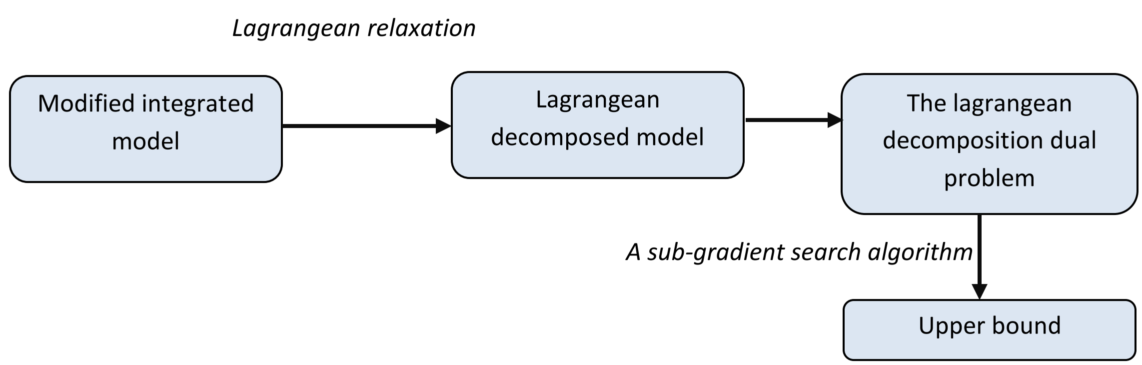


Figure 2.9: Solution method

Milind Dawande et al.[69] studied the conflict and cooperation issues arising in a supply chain where a manufacturer makes products which are shipped to customers by a distributor. They suggested two practical problems. In both problems, the manufacturer focuses on minimizing unproductive time. In the first problem, the distributor minimizes the customer cost, while in the second problem they minimize the inventory-holding cost. They evaluated the conflict cost, which is the relative in cost causing from using the other party’s optimal schedule.

Felix T. S. Chan et al.[29] developed a hybrid genetic algorithm for production and distribution problems in multi-factory supply-chain models. The analytical hierarchy process was used to organize the different criteria. The process provides a systematic approach for decision makers to assign and relate weighting. Genetic algorithms were utilized to determine jobs allocation into suitable production plants.
Jonathan Bard and Nananukul [48] developed a model which includes a single commodity, a single production facility, a set of customers with time varying demands, a finite planning horizon, and a fleet of vehicles. The delivery to a customer on a particular day could be to restock inventory, or meet the demand of that day, or both. Customer demand would be satisfied from either the inventory held at the customer sites, or from the daily distribution. A tabu search is developed for solving the problem, and a path relinking is applied to improve the results after a solution is found. An allocation model is used in the form of a mixed integer program to find feasibility solutions that serve as starting points for the tabu search. Computational testing demonstrates the effectiveness of the approach.

PIDRP (Production-inventory-distribution-routing Problem), which is similar to an inventory routing problem, but different from the traditional VRP, was investigated . They provided an effective tabu-search algorithm to find near-optimal solutions for high quality instances.

Although the three problems’ combination was considered, it could be extended to include multiple products’ situation and improved by some correct adjustments.

Mohamed Omar *et al*. [71] studied the problem of HPP (Hierarchical Production Planning) and introduced an algorithm to solve similar problems. The plan was divided into three levels, these being two mathematical models and a backwards algorithm: step one, obtain total optimal minimized costs of production, inventory, workforce and setup; then, minimize the sum of back ordering costs, penalty costs of overproduction and so on; finally, according to the results of the last levels, formulate the near-optimal sequence to minimize total weighted tardiness.

Following a study, for Dell, on how to schedule production for accepted orders enabling enough transportation time for orders to be sent by slow shipping mode to reduce the shipping cost, Kathryn E.Stecke, *et al*. [53] stated that nonpreemptive EDD (Earliest Due Date) production schedules are optimal when partial delivery is allowed. When partial delivery is not allowed, an MIP model was developed , which proved that the problem is NP-hard. They also provided an efficient heuristic algorithm to achieve a near-optimal production schedule.

A zero-inventory production and distribution problem was considered by Ronald Armstrong *et al*.[88] , whose objective was to maximize the total demands delivered by customers, chosen from a given sequence, while also satisfying other constraints (a short lifespan product, a single truck, a fixed sequence of customers with delivery time window requirements, and a limited production capacity). Its general version was proved NP-hard even with relaxed time windows and instantaneous truck travelling times. To solve the problem, they developed a heuristic lower bound on the optimal solution and a branch-and-bound procedure.

The model studied for a product with a short lifespan within an environment of a single plant, a single limited-capacity truck and the random demands from different customers. They focused on minimizing the total time that was needed for production and delivery, and for satisfying the capacity, transportation and lifespan constraints, simultaneously. With the development of a two-phase heuristic algorithm, although the optimality was obtained by comparing results from analytically derived lower bounds, this algorithm would not be effective once the truck's routing was more influenced than makespan.

Campbell and Savelsberg [6], in their work, also develop a linear time algorithm for determining a delivery schedule for a route, to define a sequence service to visit customers, which maximizes the total amount of delivery product on the route. As time delivery windows are used, flexibility of product can be adjusted; the amount of product can also be delivered to more than one target; thus the schedule of delivery to increase the amount of delivery also has flexibility. Maximum delivery quantity depends on the time of delivery windows, where the actual selection of delivery times, between the earliest and latest delivery times, will affect the total volume deliverable on a trip. The later vehicle arrives, more inventory holding capacity and more products can be delivered, and later on as consequences, the less time available to deliver because of delivery time is restricted of customers to be visited later.

They tried to divide the problem into two phases based on delivery schedule and routing problems. The first phase was to create a delivery schedule followed by a set of delivery routes, which utilizes integer programming; in the second phase, routing and scheduling heuristics were employed. They introduced the clustering system to make delivery schedules more efficient among the customers; this model involved certain restrictions. For example, all customers that require the full load capacity of a vehicle can not be combined in one cluster, also the customers whose combined inventory levels are less than the size of the vehicle capacity will not be in the same cluster, because they need a maximum load vehicle capacity within the delivery schedule. The last aspect in clustering is based on a geographical factor, ensuring the need for customers to be in close proximity to each other. In spite of clustering, they found problems inherent in route planning, thus they reduced the customer set based on the urgency of each customer, and defined them into two classes, the critical and impending customer.

Carine Cousineau-Ouimet [7], in her paper, employs a tabu research heuristic to solve the inventory-routing problem, with problem definitions where the customers demands or usage rate of customers are determined. The main idea of this method is to make use of the degradation of solution combined with the notion of memory to avoid cycling, therefore one customer will not be visited twice, or reserve exchange are tabu. The next customer who has been removed, as degradation will not be included in the routes, from there, a neighbourhood solution by given transformation is introduced; it can also be achieved by swapping customers between routes. To improve the solution, she also employs the attributes of the GENI algorithm; this method removes and inserts the customer between the other customers of a route.

Chien, Balakrishnan and Wong[9] employ lagragian relaxation, in their paper, in order to try and solve the problem between inventory routing problems and vehicle routing problems using mixed integer programming. In their model, lagragian functions to generate upper bounds and heuristic methods to obtain feasible solutions that give lower bounds for integrated problems. Later, in the paper, the problem is broken down into two sub-problems; inventory allocation and vehicle utilization. For unsatisfied customers, they become the first priority in the next period, and multiple visits to a customer are also permitted by different vehicles.

M. W. P. Savelsberg and Hwa Song[74] focus on the inventory routing problem with continuous moves, which incorporate two important real-life complexities: limited product availabilities at facilities and customers that cannot be served using out-and-back tours. Delivery routes are designed spanning several days covering huge geographic areas and involving product pickups at different facilities. They developed an integer programming based on an optimization algorithm; this optimization algorithm is embedded in local search procedures to improve solutions produced by randomized greedy heuristics.

Aghezzaf et al.[1], in their paper, discussed various models for inventory routing problems, assuming that customers' demands are stable or can be determined even in the real world where situations could lead into stochastic demand rates. However, they argue that the assumption of the usage rate of customers can be predicted over time, thus they assume demand rates of customers are stable, and take into consideration a long term cyclical inventory and distribution planning approach. The problem definition of their model is that it employs a single product, single facility and a fleet of homogenous vehicles (all with same load capacity).

S. Anily and Federgruen[92] consider a single item distribution system with one plant as a depot and a determinate number of retailers. The demand rate of each retailer is a result of the integer multiple of some base demand rate. The replenishment strategy is defined in certain regions of retailers, where there could be possible overlapping or belong to another region. Vehicles are assigned to serve in each region, and when a vehicle visits a retailer in one region, it must also visit all the retailers in that region.

They state that inventory can only be held at the retailers; however, they later extend this to say that inventory can also be held at central warehouses or distribution centres.

Pankaj Chandra and Fisher[82] have demonstrated the integration of production and distribution decisions, which presents a challenging problem for manufacturers trying to optimize their supply chain. At the planning level, the immediate goal is to coordinate production, inventory, and delivery needs to meet customer demand so that the corresponding costs are minimized. Achieving this goal provides the foundations for streamlining the logistics network and for integrating other operational and financial components of the system. In this paper, a model is presented, which includes a single production facility, a set of customers with time varying demands, a finite planning horizon, and a fleet of vehicles for making the deliveries. Demand can be satisfied from either inventory held at the customer sites, or from daily product distribution. In the most restrictive case, a vehicle routing problem must be solved for each time period. The decision to visit a customer on a particular day could be to restock inventory, meet that day's demands, or both. In a less restrictive case, the routing component of the model is replaced with an allocation component only. A procedure centring on reactive tabu search is developed for solving the full problem. After a solution is found, path relinking is applied to improve the results. A novel feature of this methodology is the use of an allocation model, in the form of a mixed integer program, to find good feasible solutions that serve as starting points for the tabu search. Lower bounds on the optimum are obtained by solving a modified version of the allocation model.

Liu and Lee[59] explained that multi-depot location routing problem and combined depot location and vehicle routing decisions, in order to determine the locations of depots and find the optimal set of vehicle schedules and routes. Inventory control decisions are interrelated with vehicle routing and depot location; however, the inventory control decisions are always ignored. A mathematical model for the single-plant multi-depot location-routing problem, taking inventory control decisions into consideration, is proposed.

Anna Maria Sarmiento and Rakesh Nagi[4] referred to an integrated analysis of production-distribution systems, and identified important areas where further research is needed. By integrated analysis is reached understand analysis performed on models that integrate decisions of different production and distribution functions for a simultaneous optimization. It is reviewed work that explicitly considers the transportation system in its analysis, with particular emphasis on the following questions: (i) how have logistics aspects been included in the integrated analysis? (ii) What competitive advantages, if any, have been obtained from the integration of the distribution function to other production functions within a plant? Production and distribution operations are the two most important operational functions in a supply chain. To achieve optimal operational performance in a supply chain, it is critical to integrate these two functions and plan and schedule them, jointly, in a coordinated way.

Daskin[15] pointed out that there were interrelated decisions, which were involved in the LRP. These decisions include: (i) how many facilities to locate, (ii) Where the facilities should be, (iii) Which customers to assign to which warehouses, (iv) In what order customers should be served on each route. The LRP is categorized as NP (Non Polynomial) – hard problems, which involve two NP-hard problems (facility location and vehicle routing) and it is modelled as a combinatorial optimization problem (Nagy and Salhi[74]). From their papers review, some practical applications of LRP were summarized; for example, blood bank location (Cohen and Pierskalla[13]).

Min *et al*.[16] and Nagi and Salhi[76] studied the variety and classification of LRP, dividing it into its problems' perspective and the solution method. Their review was summarized by Kalkan[52] in the table (5.1).

Eugeniusz Nowicki and Smutnicki[27] provided a special method, based on tabu search, for minimizing the maximum makespan in the flow shop problem. Due to the reduced structure of the neighbourhood and due to a special method of calculating makespan, the method works faster and more efficiently than other known algorithms. The essence of the algorithm consists in exploiting properties, which has allowed them to search (using the makespan) the most interesting part of a single neighbourhood in the mean time $O(n^{1.11}m^{1.10})$ on tested instances. The proposed method solves, almost optimally, medium and large size instances on a PC in a short time. The method is easily implemented and is easily tuned (default values of tuning parameters are recommended).
Meral Azizoglu, Cakmak and Kondakci[66] have considered the problem of minimizing total flow time in a flexible flow shop problem. They proposed lower and upper bounding

schemes and incorporated them into a branch-and-bound algorithm using two branching schemes. Their computational experience showed that the algorithm is capable of generating optimal solutions for medium-sized problems. The branch-and-bound algorithm produces the optimal solution at very early stages and the majority of the time is spent in illustrating that the solution is optimal. A branch-and-bound algorithm that terminates after a prespecified time limit maybe an attractive heuristic solution for larger size problems if proving the optimality of the solution is not crucial. The model they studied can be generalized to include due-date-related performance measures and/or flexible job shops.

The main aim of the research of Colin R. Reeves[14] was to explore the potential of genetic algorithms for flow shop sequencing. However, as a subsidiary observation he notes that for certain types of problems, it may not be worth using sophisticated procedures, as a simple neighbourhood search can obtain solutions of comparable quality very easily. This dependence of solution quality on problem structure in combinatorial optimization is not one that has been adequately addressed in the literature. For problems where structure is not apparent, a naive method does less well, and we would make the following observations in respect to the other methods.

The overall implication of his studies carried out is that simulated annealing algorithms and genetic algorithms produce comparable results for flow shop sequencing problems of most sizes and types of problem, but that genetic algorithms will perform relatively better for larger problems, and they will reach a near-optimal solution rather more quickly.

Moreover, it should be pointed out that the Potts simulated annealing algorithm heuristic is the result of a substantial amount of experimentation in order to arrive at the parameter settings recommended. No experimentation of this kind has, as yet, been done on the genetic algorithm heuristic reported here; the parameters were simply set at what seemed "sensible" values after some rather small-scale experiments on one parameter at a time using some 20/5 problems. One of the characteristics of genetic algorithms is their robustness in respect of parameter settings, so that a similar performance might be expected from a wide range of choices of population size, mutation rate and so on. Nevertheless, there is some experience that would suggest that worthwhile gains might be achieved by trying to optimize in parameter space. Of course, it is possible that another type of genetic algorithm might do even better; in particular it should be pointed out that this implementation is a "pure" genetic algorithm, i.e., no problem-specific information is used. Hybrid genetic algorithms have been suggested, where use is made of such information may perform better. All these factors are being investigated. Furthermore, genetic algorithms lend themselves very well to parallel implementation: there is no reason why the evaluation of new chromosomes needs to be done sequentially; this method would further accelerate solution times. A parallel version of the genetic algorithm, described above, is also being explored.

In conclusion, genetic algorithms provide a variety of options and parameter settings, which still have to be fully investigated. This research has demonstrated the potential for solving machine-sequencing problems by means of a genetic algorithm, and it clearly suggests that such procedures are well worth exploring in the context of solving large and difficult combinatorial problems.

Chung-Yee Lee and Chen[10] studied a machine scheduling problem with explicit transportation considerations. They considered two models of transportation: the first model involves transporting semi-finished products from one machine to another; the second model considers delivering the finished goods to the final customers or warehouse. The transportation times and capacity are considered. They developed a dynamic programming model to solve the problem.

The best-known heuristic for the general flowshop scheduling problem with makespan minimization is NEH, due to Nawaz et al. This procedure consists of inserting a job into the best available position of a set of partially scheduled jobs: i.e., in the position that would cause the smallest increment to the value of the makespan. [77]

In their paper, M. Ben-Daya and Al-Fawzan[63] proposed a tabu search algorithm for the flowshop scheduling problem. The proposed algorithm suggests simple techniques for generating neighbourhoods of a given sequence and a combined scheme for intensification and diversification. They used the NEH algorithm for the initial solution. They compared the results used benchmark test problems and other literature for which lower bounds are known. An average deviation of less than 9% from the lower bound was achieved.

E. Taillard[26] compared some efficient heuristic algorithms to solve the flowshop problem and used a tabu search algorithm to improve the complexity of the best one. Computational experiments were reported. He compared the CPU time and number of iterations required to solve the same problems. He found that the NEH algorithm was the best algorithm among those tested.

Tiago et al.[104] considered the permutation flowshop scheduling problem with blocking in-process. There were no buffers between successive machines. They proposed a genetic algorithm to solve this problem. The performance of the algorithm was tested and compared with other algorithms. They used the NEH algorithm to generate the initial solution.

S. G. Ponnambalam et al.[95] used the tabu search technique to solve the job shop scheduling problem, with makespan minimization criteria. They used the adjacent pairwise interchange method to generate neighbourhoods. They compared the results with simulated annealing and genetic algorithms. The performance of the used algorithm is comparable. Out of 25 problems considered, the tabu search performs better for six problems. For the remaining problems, the tabu search results are very close to both algorithms' results.

3. Manufacturer Dominates

The manufacturer has his own ideal schedule. This schedule is determined by cost and capacity considerations. Using this ideal schedule without consideration for other schedules leads to poor overall performance measure. In this chapter, the scenario considers the optimal schedule for the manufacturer. The manufacturer tries to minimize the total production cost (in this case it is equal to setup cost) per distribution cycle (which is considered one week).

3.1 Flow shop models

Flow shop (FS) scheduling is one of the most important problems in the area of production management. It can be briefly described as follows: There are a set of *m* machines (processors) and a set of *n* jobs. Each job comprises a set of *m* operations which must be done on different machines. All jobs have the same processing operation order when passing through the machines. There are no precedence constraints among operations of different jobs. Operations cannot be interrupted and each machine can process only one operation at a time. The problem is to find the job sequences on the machines which minimizes the makespan, i.e. the maximum of the completion times of all operations. As the objective function, mean flow time, completion time variance and total tardiness can also be used. The flow shop scheduling problem is NP-hard and thus it is usually solved by approximation or heuristic methods. Figure 3.1 shows the generalized flowshop problem.

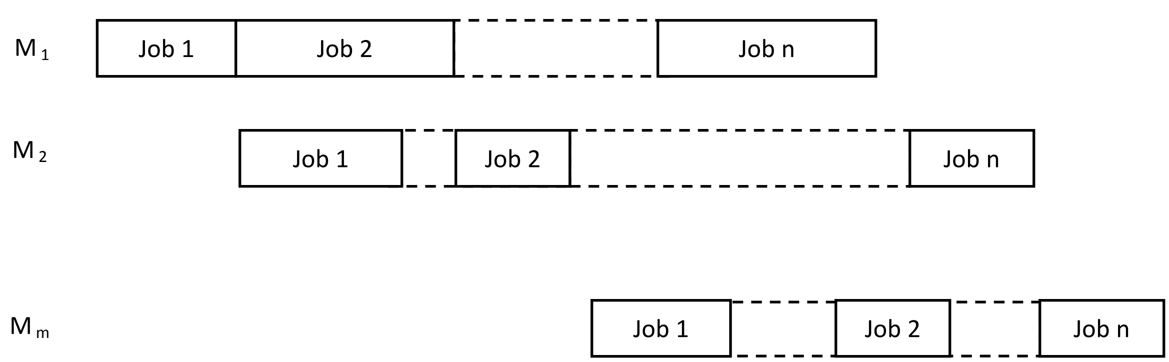


Figure 3.1: Generalized flow shop problem

The three-field notation $\alpha|\beta|\gamma$ is used to describe all details of considered flow shop problem variants.

The α field denotes the shop configuration (indicates the structure of the problem), including the shop type and machine environment per stage. The α field discomposes into four parameters, i.e. α1, α2, α3, α4. Here, parameter α1 indicates the considered shop, and parameter α2 indicates the number of stages.

For each stage, parameters α3 and α4 indicate the machine set environments. More specifically, α3 indicates information about the type of the machines while α4 indicates the number of machines in the stage.

Usually, all queues are assumed to operate under the First In First Out (FIFO) discipline, that is, a job cannot ”pass” another while waiting in a queue. If the FIFO discipline is in effect the flow shop is referred to as a permutation (prmu) flow shop and the β field includes the entry prmu. For example, as Fm | prmu | Cmax (see Fig.3.2) is one of the more basic scheduling problems, it has attracted a great deal of attention over the years. Many heuristics have been developed for dealing with this problem.

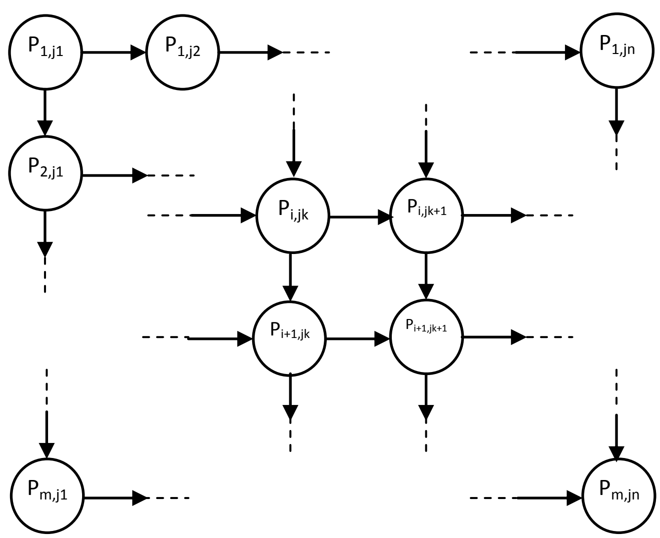


Figure 3.2: Directed Graph for the Computation of the Makespan in Fm | prmu | Cmax under sequence j1, . . . , jn.[72]

The possible machine set environments on the stage i of a flowshop scheduling (FS) are:

1. Single machine (1): a special case; any stages (not all) in a FS can have only one machine;
2. Identical machines in parallel (Pmi): job j may be processed on any of mi machines;

3. Uniformed machines in parallel (Qmi): the mi machines in the set have different speeds; a job j may be processed on anyone machine of set, however its processing time is proportional of the machine speed;
4. Unrelated machines in parallel (Rmi): a set of mi different machines in parallel. The time that a job spends on a machine depends on the job and the machine.

When there are several consecutive stages with the same machine set environments, the parameters α3 and α4 can be grouped as ((α3α 4(i))i = sk), where s and k are the index of the first and the last consecutive stage, respectively. For example, the notation FH4, (1,(P2(i))i=23,R3(4)) refers to a FS configuration with four stages where there are one machine at the first stage, two identical machines in parallel at second and third stages and three unrelated parallel machines in the fourth stage. [46]

β field cumulates a set of explicit constraints (not implied by the internal semantic structure – for example, for flow shop, a job cannot start its execution on a machine if it's still under processing on the previous one); in another way the β field provides the shop properties; also other conditions and details of the processing characteristics, which may enumerate multiple entries, also may be empty if they are not.

3.2 Classification of Scheduling Problems

French[31] introduced the target of the general scheduling problem is to find a sequence, in which the jobs (tasks) pass between the resources (machines), which is a feasible schedule, and optimal with respect to some performance criterion. Graves[2] introduced a functional classification scheme for scheduling problems. This scheme categorizes problems using the following five dimensions:

- **Requirement generation**

Based on requirements generation, it can be classified as an open shop or a closed shop. An open shop is "build to order" and no inventory is stocked and when orders are filled from existing inventory it is called closed shop. Closed shop can further be classified into job shop and flow shop. A detailed classification of scheduling problems is shown in following figure.

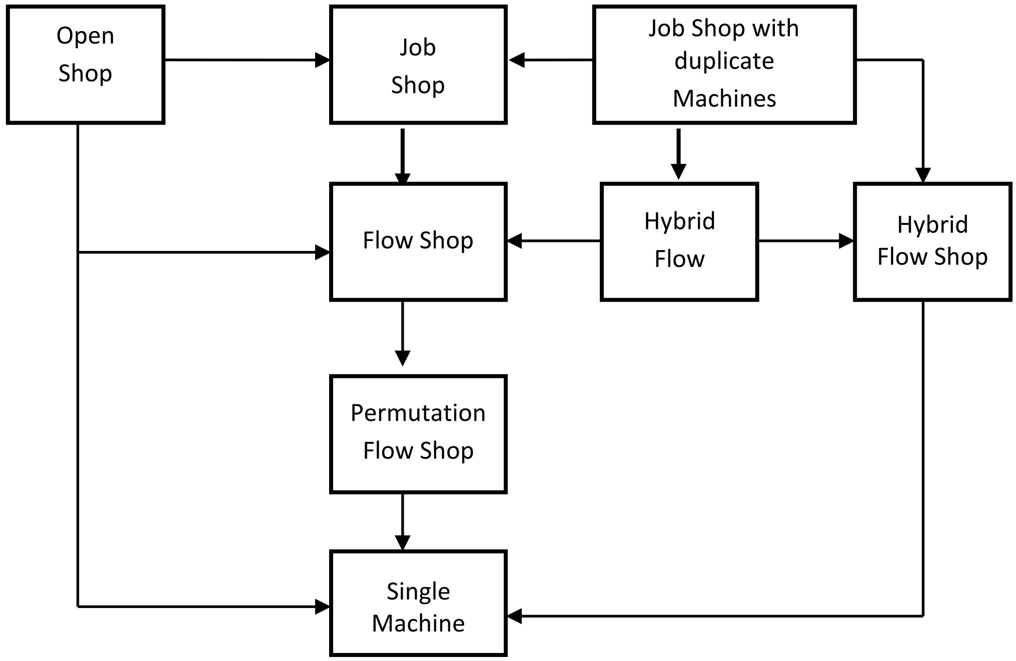


Figure 3.3 Classification of scheduling problems based on requirement generations[18].

- **Processing complexity**

Processing complexity refers to the number of processing steps and workstations associated with the production process. This dimension can be decomposed further as follows:

- One stage, one processor;
- One stage multiple processors;
- Multistage flow shop;
- Multistage job shop.

The one stage, one processor and one stage, multiple processors problems require one processing step that must be performed on a single resource or multiple resources respectively. In the multistage, flow shop problem each job consists of several tasks, which require processing by distinct resources; but there is a common route for all jobs. Finally, in the multistage, job shop situation, alternative resource sets and routes can be chosen, possibly for the same job, allowing the production of different part types.

- **Scheduling criteria**

Scheduling criteria, states the desired objectives to be met. “They are numerous, complex, and often conflicting”. Some commonly used scheduling criteria include the following: minimize total tardiness, minimize the number of late jobs, maximize system/resource utilization, minimize in-process inventory, balance resource usage, maximize production rate etc.

- **Parameter variability**

The dimension ‘parameters variability’ indicates the degree of uncertainty of the various parameters of the scheduling problem. If the degree of uncertainty is insignificant (i.e. the uncertainty in the various quantities is several orders of magnitude less than the quantities themselves), the scheduling problem could be called deterministic. For example, the expected processing time is six hours, and the variance is one minute. Otherwise, the scheduling problem could be called stochastic.

- **Scheduling environment**

The dimension, scheduling environment, defined the scheduling problem as static or dynamic. Scheduling problems in which the number of jobs to be considered and their ready times are available are called static. On the other hand, scheduling problems in which the number of jobs and related characteristics change over time are called dynamic.

3.3 FSPs with setup times

The setup times is a subset of cycle time, defined as a period which is needed to carry out an initial format which usually will be necessary before adding a new job on each machine. So before adding any new jobs to be processed on the machines there is a need to prepare the machine to be ready for the new task, and this preparation requires time intervals which vary from job to another, and from machine to another (although it depends on the previous job even if it is the first job in the machine).

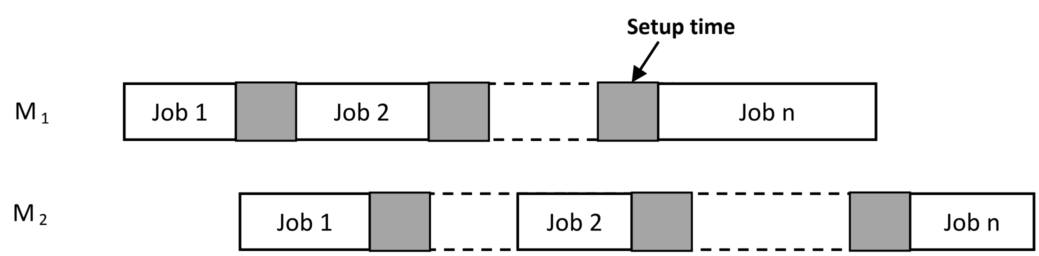


Figure 3.4 Flowshop with setup time

In some cases the production doesn't required setup time, so it can included in the processing times as negligible values (set as zeros).

We can divide the setup time to two categories:

- Non-separable setup times are either included in the processing times or are negligible, and hence are ignored.
- Separable setup times are not a part of processing operation.

However, in general the structure of the breakdown time when a job belongs to a machine is as follows :[72]

- Setup time that is independent on the job sequence. This operation consists of activities such as fetching the required details, and fixtures, and setting them up on the machine.
- Setup time that is dependent on the job to be processed. The carrying out of this operation includes the time required to put the job in the jigs and fixtures and to adjust the tools.
- Processing time of the job being processed.
- Removal time that is independent on the job that has been processed. This operation includes activities such as dismounting the jigs, the fixtures and/or tools, inspecting/sharpening of the tools, and cleaning the machine and the adjacent area.
- Removal time that is dependent on the job that just has been processed. This operation includes activities such as disengaging the tools from the job, and releasing the job from the jigs and fixtures.

Among scheduling problems which consider separable setup times in parallel machine environment, there is a class of problems of a high computational complexity, where setup from one product to another occurs on a machine; and machine parameters, which have to be changed during a setup, differ according to the production sequence. It leads to sequence-dependent setup times and consequently to sequence-dependent setup costs.

Every job is to be processed on one machine at a time without preemption and a machine processes no more than one job at a time. When an operation is started on a machine, it must be finished without interruption.

Typically, buffers are located between stages to store intermediate products.

The problem consists of assigning the jobs to machines at each stage and sequencing the jobs assigned to the same machine so that some optimality criteria are minimized. The following index are used for describing the problems: j for job, j = 1,…, n, i for stage,

i = 1, 2, …, k; mi for number of machines at the stage i; l for machine index, l = 1, 2, …, mi.

There are many algorithms to solve FSP with setup time. The algorithm used in this thesis is NEHT-RB algorithm. This is a modified version of a heuristic (NEH) proposed by Nawaz et al., and NEHT-RB is extended from the NEH heuristic to handle setup times.

Appendix III shows the randomized algorithm, while Appendix IV shows the comparison results of the NEH algorithm, randomized algorithm and a shortest-processing-time-first (SP) algorithm. Figures a, b, and c in Appendix IV show the results for 10*20 (10 machines, and 20 jobs), 10*50, and 10*100 problems. The number of runs was ten in every model.

It is obvious that NEH works better than the other algorithms, especially when the problem contains a big number of jobs.

The main idea of NEH algorithm is to generate an initial order of jobs with respect to an indicator value, then insert the jobs iterative into a partial sequence according to the initial order of the first stage.

The construction of NEHT-RB is as follows:

Step 1: Sequence the jobs by using a particular sequencing rule (first-stage sequence).

Step 2: Assign the jobs to the machines at every stage using the job sequence from either the First-In-First-Out (FIFO) rule or the Permutation rule.

Step 3: Return the best solution.

The best known heuristic for the general flowshop scheduling problem with makespan minimization is NEH, due to Nawaz et al[77]. This procedure consists of inserting a job into the best available position of a set of partially scheduled jobs; i.e., in the position that would cause the smallest increment to the value of the makespan. [86]

The NEHT-RB idea of building a feasible schedule is very simple. At each iteration of the algorithm there is a partial schedule S. A job h is selected from a priority list P of unscheduled jobs. Nawaz et al. suggest a largest processing time (LPT) rule; i.e., a list where the jobs are ordered from largest to smallest total processing time. The partial schedule S and the job h define a unique greedy function ψ(j): { 1.2.. , |S + 1|} → R, where ψ(j) is the makespan of the new schedule S' resulting from inserting job h at the j^{th} position (right before the j^{th} job) in S. Here, position |S + l| means an insertion at the end of the schedule. Job h is inserted into position

k = argminij=l.....|S + l| {ψ(j)}

where the position in S has the minimum makespan value.

The Procedure NEHT-RB is as follows:

Input: Set P of unscheduled jobs.

Output: Feasible schedule S.

Step 0. Set S = 0

Step 1. Sort the jobs in P to form an LPT priority list

Step 2. while |P| > 0 do

Step 2a. Remove h, the first job from P

Step 2b. Compute ψ(j) for every position j = 1, …., |S|

Step 2c. Find k = argminj{ψ(j)}

Step 2d. Insert job h at position k in S

Step 3. Output S

Step 4. Stop

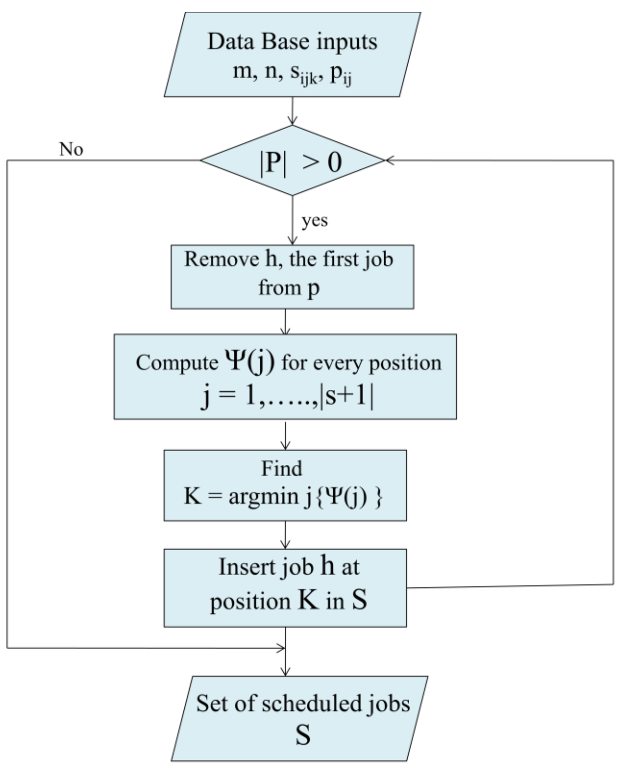


Figure 3.5: NEHT-RB algorithm

Using this algorithm, initial solution for job schedule can be calculated. The next step is to improve this solution using tabu search. To generate the neighborhood, more than one idea is used. The first one is swapping. Given a sequence *s*, let *i* and *j* be two positions in the sequence *s*. A neighbor of s is obtained by interchanging the jobs in positions *i* and *j*. The positions *i* and *j* selected randomly. Figure 3.6 shows this criteria.

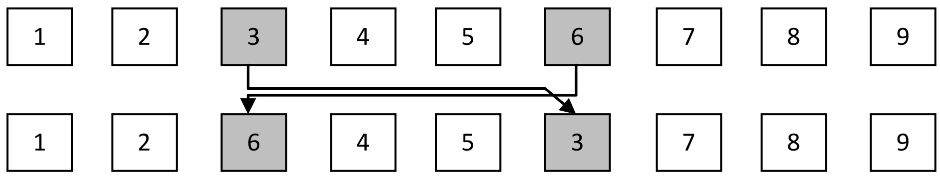


Figure 3.6: Swapping criteria

The second criteria is Insertion. Given a sequence *s*, let *i* and *j* be two positions in the sequence *s*. A neighbor of *s* is obtained by inserting the job in position *i* in position *j*. Positions *i* and j are selected randomly. Figure 3.6 shows this criteria.

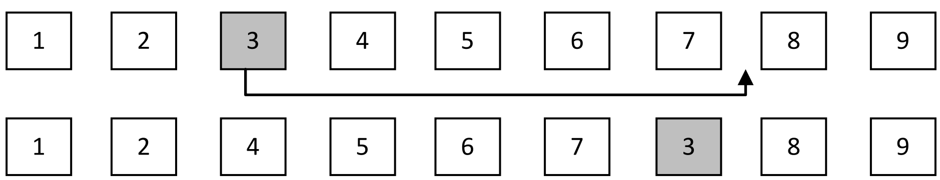


Figure 3.7: Insertion criteria

The third way is block insertion. Given a sequence s, let *i*, *j*, and *k* be three integers. A neighbor of *s* is obtained by inserting a bloc of *k* jobs starting at job *i* in position *j,* Figure 3.7. The positions *i* and *j* and the integer *k* are randomly selected.

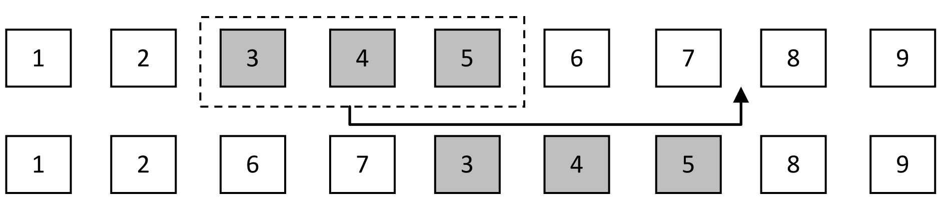


Figure 3.8: Block Insertion criteria

The last criteria used is Block Swapping. Given a sequence s, let *i* and *j* be two positions in the sequence *s*. A neighbor of s is obtained by interchanging bloc of *k* jobs starting at job *i* in position *j,* as shown in figure 3.9. The positions *i* and *j* and the integer *k* are selected randomly.

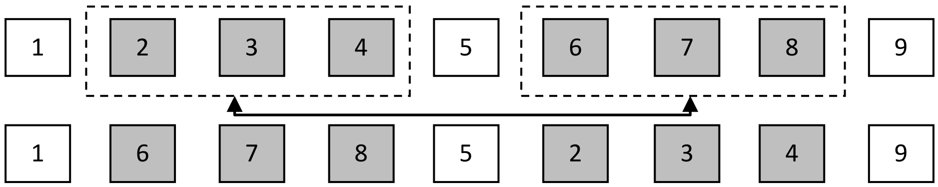


Figure 3.9: Block swapping criteria

The objective function is the makespan. Thus, simply define 'best' by reference to the objective function and the current tabu conditions, the best neighbor in the candidate list is the sequence that yields the smallest makespan subject to not creating a tabu move. The tabu list size used is 7.

The algorithm is stopped when there is no improvement between two consecutive calls of the diversification scheme. Other criteria could be used such as stopping after some maximum number of iterations or stopping after some maximum number of calls of the diversification scheme. The optimal solution is obtained.

The distributor have to use this schedule to calculate his own schedule. The suggested algorithm is a Vendor Managed Inventory model. According to this model the total distance and total inventory is calculated.

Table 3.1 shows a comparison of results for an example for 10 machines and different number of jobs. The quality of the solution is calculated by the objective function (makespan Cmax) and CPU time (in seconds).

Table 3-1: Compression between tabu search neighborhoods criteria for 10 machines

10 machines	Initial solution	Element Insertion		Block Insertion		Block Swapping		Pair Swapping	
Jobs	Cmax	CPU	Cmax	CPU	Cmax	CPU	Cmax	CPU	Cmax
10	141	1	139	1	139	3	139	<1	136
20	216	1	215	1	213	12	213	1	211
25	264	1	261	1	261	19	262	1	261
30	300	1	299	1	299	30	300	1	299
40	382	1	382	2	381	51	382	2	381

3.4 VMI Mathematical Model

The three-echelon inventory and distribution routing system considered in this thesis consists of a single plant producing multiple products. The manufactured products have to be delivered to depots by vehicles at the plant to ensure fulfillment of demand, which is considered deterministically known over a planning horizon. On the other hand, retailers will be replenished by their respective depot with different products transported by means of vehicles at each depot. Either plant or depot has limited storage capacity and its own truck for transportation. Transportation costs of these vehicles are proportional to the travelling time. There is no fixed cost associated with vehicle usage. It is assumed that each truck can make multiple trips (a trip is defined as a sequence of retailer locations a vehicle visits, starting from a depot and ending at the same depot) during each time period as long as it can return to the base depot at the end of the same period. The objective is to minimize the total inventory and transportation costs, while fulfilling the demand requirement.

To give a formal presentation of the Integrated Inventory and Distribution Routing Problem in a VMI system, a supply chain environment with the following assumptions is considered:

- Single plant
- Multiple depots
- Multiple retailers
- Multiple products
- Multiple time periods within a planning horizon
- A number of vehicles at plant
- A number of vehicles at each depot
- Each vehicle can visit more than one customer during a trip, and can make multiple trips within one period if possible
- Each vehicle returns to its base plant or depot at the end of each period

Notations and variables:

Parameter definitions for the IRP model

Symbol	Definition
m	distribution cycle (t=1,2,3……m)
T	distribution cycle time (one week)
P	plant
l	distribution center ($d=d_1,d_{2,\ldots\ldots}d_l$)
n	retailers (r=1,2,3…..n)
N	product (i=1,2….N)
d_{irt}	demand of retailer r for product i at time t
I_{irt}	inventory level of retailer r for product i
I_{idt}	inventory level of the depot for product i
I_{ipt}	inventory level of the plant for product i
q_{irt}	quantity of product i distributed from depot to retailer r
q_{idt}	replenished quantity of product i from plant to depot
q_{ipt}	produced quantitiy of product i at plant
α_{dt}	1 or 0, when q_{idt} >0 or otherwise
β_{rt}	1 or 0, when q_{irt} >0 or otherwise
C_{hip}	unit inventory holding cost for product i at plant
C_{hid}	unit inventory holding cost for product i at depot
C_{hir}	unit inventory holding cost for product i at retailer
d_{xy}	total distance for route y which belongs to depot d (x=1,2……n, y=1,2……n)
d_{pd}	distance between plant and depots ($d= d_1,d_{2,\ldots\ldots}d_l$)

C_v	variable transportation cost in unit distance

Variable definitions for the IRP model

Symbol	**Definition**
C_{Thp}	total holding cost for plant
C_{Thd}	total holding cost for depot
C_{TTd}	total transportation cost for depot
C_{Thr}	total holding cost for retailer
C_{TTr}	total transportation cost for retailer

The integrated inventory and distribution routing problem can then be formulated as follows:

minimizing total cost = min (inventory cost of all products at the plant + Inventory cost at DC's + transportation cost from the plant to DC's + inventory cost at retailers + transportation cost from DC's to retailers).

$$\min \sum_{t=1}^{m}\sum_{i=1}^{N} C_{hip}\frac{I_{ipt-1}+I_{ipt}}{2} + \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{d=1}^{l} C_{hid}\frac{I_{idt-1}+I_{idt}}{2} + \sum_{t=1}^{m}\sum_{d=1}^{l} 2C_v d_{pd}\alpha_{dt} + \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{r=1}^{n} C_{hir}\frac{I_{irt-1}+I_{irt}}{2} + \sum_{t=1}^{m}\sum_{x=1}^{d}\sum_{y=1}^{n} C_v d_{xy}\beta_{rt} \tag{3.1}$$

s.t.

Total holding cost for the plant:

$$C_{Thp} = \sum_{t=1}^{m}\sum_{i=1}^{N} C_{hip}\frac{Iipt\text{-}1+Iipt}{2} \tag{3.2}$$

$$I_{ipt} = I_{ipt-1} + q_{ipt} - \sum_{d=1}^{l} q_{idt} \quad \forall\ i, t,\ i\in N,\ t\in T\ p=1 \tag{3.3}$$

Total holding cost for depot:

$$C_{Thd} = \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{d=1}^{l} C_{hid}\frac{I_{idt-1} + I_{idt}}{2} \quad (3.4)$$

$$I_{idt}=I_{idt-1} + q_{idt} - \sum_{r=1}^{n} q_{irt} \ , \quad \forall\ i, t, i \in N, t \in T \quad (3.5)$$

Total transportation cost for depot

$$C_{TTd} = \sum_{i=1}^{m}\sum_{d=1}^{l} 2C_v d_{pd}\alpha_{it} ,\ \alpha_{it} \in \{0,1\} \quad \forall\ i, t, i \in N, t \in T \quad (3.6)$$

Total holding cost for retailer

$$C_{Thr}= \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{r=1}^{n} C_{hir}\frac{Iirt\text{-}1+Iirt}{2} \quad (3.7)$$

$$I_{irt} = I_{irt-1} + q_{irt} - d_{irt} \quad \forall\ i, t, \ \forall\ i, t, i \in N, t \in T, r \in n \quad (3.8)$$

Total transportation cost for retailer

$$C_{TTr} = \sum_{t=1}^{m}\sum_{x=1}^{d}\sum_{y=1}^{n} C_v d_{xy}\beta_{rt}, \qquad \beta_{rt}\epsilon\ \{0,1\}\ \forall\ t, t\in T, r \in n \quad (3.9)$$

Storage capacity and safety stock requirement constraints

The maximum stock at the plant, DC's and retailers should not exceed the maximum storage capacity.

$$0 \le I_{ipt} \le I_p^{max} \quad \forall\ i, t, i \in N, t \in T \quad (3.10)$$

$$0 \le I_{idt} \le I_d^{max} \quad \forall\ i, t, i \in N, t \in T \quad (3.11)$$

$$0 \le I_{irt} \le I_r^{max} \quad \forall\ i, t, i \in N, t \in T \quad (3.12)$$

Non-negative and integer requirement

$$q_{irt} \ge 0\ q_{idt} \ge 0\ \ q_{ipt} \ge 0 \ \forall\ i, t, i \in N, t \in T \quad (3.13)$$

The objective function (3.1) of the model includes inventory cost (at plant, depots and retailers, respectively), and transportation cost (both plant and depots owned vehicles).

Constraints (3.2) and (3.3) assure the balance at the plant among production, inventory and delivery, and the demand fulfillment for depot respectively. Constraint (3.2) is the average inventory level at plant. Constraint (3.3) is the inventory balance constraint at plant, which requires that distribution from the plant can be met from inventory and current production in that period. Constraints (3.4) and (3.5) assure the balance at the depot among replenishment, inventory and delivery, and the demand fulfillment for retailers respectively. Constraint (3.4) is the average inventory level at depot. Constraint (3.5) is the inventory balance constraint at depot, which requires that distribution from the depot can be met from inventory and replenishment from plant in that period. Constrain (3.6) is the transportation cost for depot including variable cost and fixed cost when one delivery is placed from plant to depot. Constraints (3.7) and (3.8) assure the balance at the retailer among replenishment, inventory and delivery, and the demand fulfillment for customers respectively. Constraint (3.7) is the average inventory level at retailers. Constraint (3.8) is the inventory balance constraint at retailers, which requires that demand from customers will be met from inventory and replenishment from depot in that period. Constrain (3.9) is the transportation cost for retailers including variable cost and fixed cost when one replenishment is placed from depot to retailers. Constraints (3.10), (3.11) and (3.12) are inventory constraints satisfying maximum storage capacity and inventory requirements at plant, depots and retailers. And finally, constraint (3.13) is non-negative constraints.

3.5 VMI Heuristic Algorithm

In general, the VMI model tasks can break off into 2 sub-tasks, later called phases, where each phase has a relationship with the others.

Phase I is setting a service sequences list for each customer; in the next step in phase II, the route selection based on urgency case customer from phase I can be added to accomplish the vendor-managed inventory activity.

Since avoiding a lack of stock is the main objective, three aspects have to be considered:

- When do the articles have to be delivered to the customers?
- How many articles have to be delivered?
- Which routes have to be taken to serve delivery action?

Delivery times is one of the most important aspects in vendor-managed inventory. Some data required to calculate this time are:

- Usage rate of the customer per day
- Stock out time of each customer
- Inventory level of each customer.

Usage rate of the customer is a very important element to know how quickly the distribution centre can take action to deliver the article to the customer, and the time to deliver the goods to avoid stock out. Usage rate, inventory capacity and stock out time are strongly related to delivery time. The number of customers also affects the model. A larger number of customers means more complex situations have to be handled. Also, more distribution centres with different locations requires more flexibility to fulfil these customers' demands.

Delivery quantity is the answer to the question of how many articles have to be delivered to each customer. The amount of delivery depends on how fast the customer consumes the product and how big their inventory capacity is. If the customer only has a small inventory capacity and the usage rate is fast during work hours, this means that the vendor has to visit the customer more often with small delivery periods. It means that we cannot maximize our delivery quantity. One aspect we have to consider is that delivery quantity cannot exceed the inventory capacity of the customer.

Figure 3.10 illustrates that, if we want to maximize delivery quantity, the total amount of delivery in one route schedule between the customers in this route has to be able to utilize vehicle capacity.

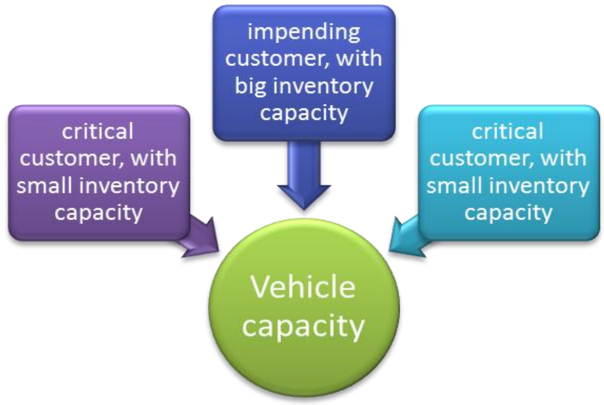


Figure 3.10. Example of Delivery Quantity

Defining the route schedule in VMI is not so flexible compared to VRP, since VMI is based on the urgency of the customers. In the case of VMI, we cannot select certain routes to minimize the distance to the customer; VMI more concerns how to serve the customer as soon as possible to prevent stock out. For example, although we have customers near the distribution centre who do not need replenishment in a short time, we have to serve customers in critical term first based on the service sequences list (SSL). In VMI, distance does not matter as long as the vendor can fulfil the demand of the customer. Certainly, some conditions in practical terms could also be acceptable; for example, if two customers have the same urgency (same value in the SSL) and they are on the same route, then the vehicle will deliver the goods to the nearest one first. Figure 3.11 gives some explanation of this idea.

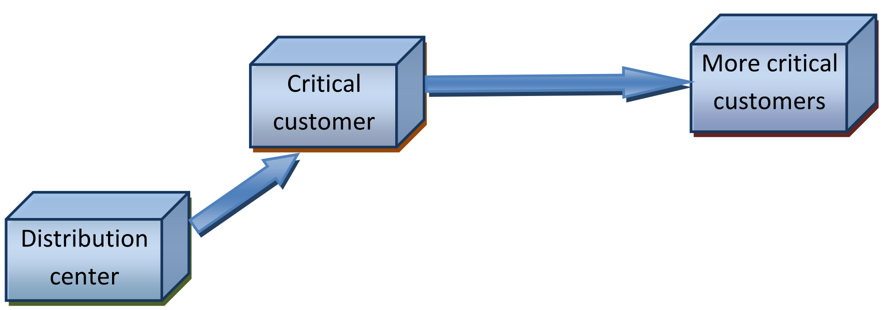


Figure 3.11. Example of Route Selection

There are some conditions that can affect the route selection; among them are:

- Geographical advantage

- Amount of service vehicles
- Vehicle capacity.

Geographical advantage is the distance between distribution centre and customers, or among the customers themselves. For closer customers it is possible to assign a more flexible route, although the route schedule still has to refer to the service sequences list, as already explained above.

The number of vehicles that the plant or distribution centre has can give more advantages in setting the route selection; more vehicles means more flexibility in assigning the customers to the routes.

Vehicle capacity is also an important factor when making the route schedule. A bigger capacity of the vehicle means that the vehicle can deliver more quantity, and can also move further to the next customer.

In this thesis, a three-phase methodology Route-Route-Cluster to solve M-M (multi-depot and multi-retailer) problem is investigated. Figure (3.12) shows a schematical representation of the system.

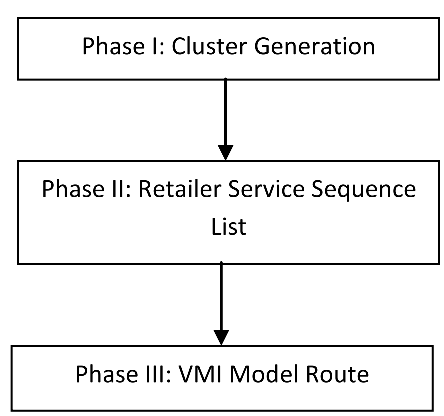


Figure 3.12: A schematical Model of the distribution system

As shown in figure 3.12, it is clear that this method is divided into three stages including specific steps respectively.

In stage 1, the main objective is to group retailers and depots into different clusters according to available data and assumptions. For the method of grouping, the nearest neighbor algorithm and stem distance are chosen. In stage 2, the service sequence list, which plays an important role in stage 3, is created based on the stock out time of products according to the sequence from small to large. In stage 3, which route to choose and how to assign vehicles are the main tasks. According to the service sequence list created in former stage, trucks are sent out to transport based on the premises that the delivery quantity is not allowed to exceeding the capacity of vehicle on the one hand. On the other hand, when one truck can not serve some retailer in urgent situation, a new route for this retailer need to be created to avoid causing shortage.

3.5.1 Phase I: Cluster generation

Based on the location, retailers are routed into separate route by regarding the individual average demand of retailers and storage capacity of depots. (Figure 3.13)

This phase takes the following steps.

STEP 1: Calculate the total demand of all the retailers in a planning horizon and allocate it evenly into each depot (assumed all the depots has the same capacity)

$$U_{total} = \sum_{r=1}^{r} U_r$$

U_{total}: total demand of all the retailers

U_r: individual customer demand

$Q_{DC}= U_{total}/n$

Q_{DC}: assigned quantity to each depot

n: number of depots (supposed the depot has the same capacity)

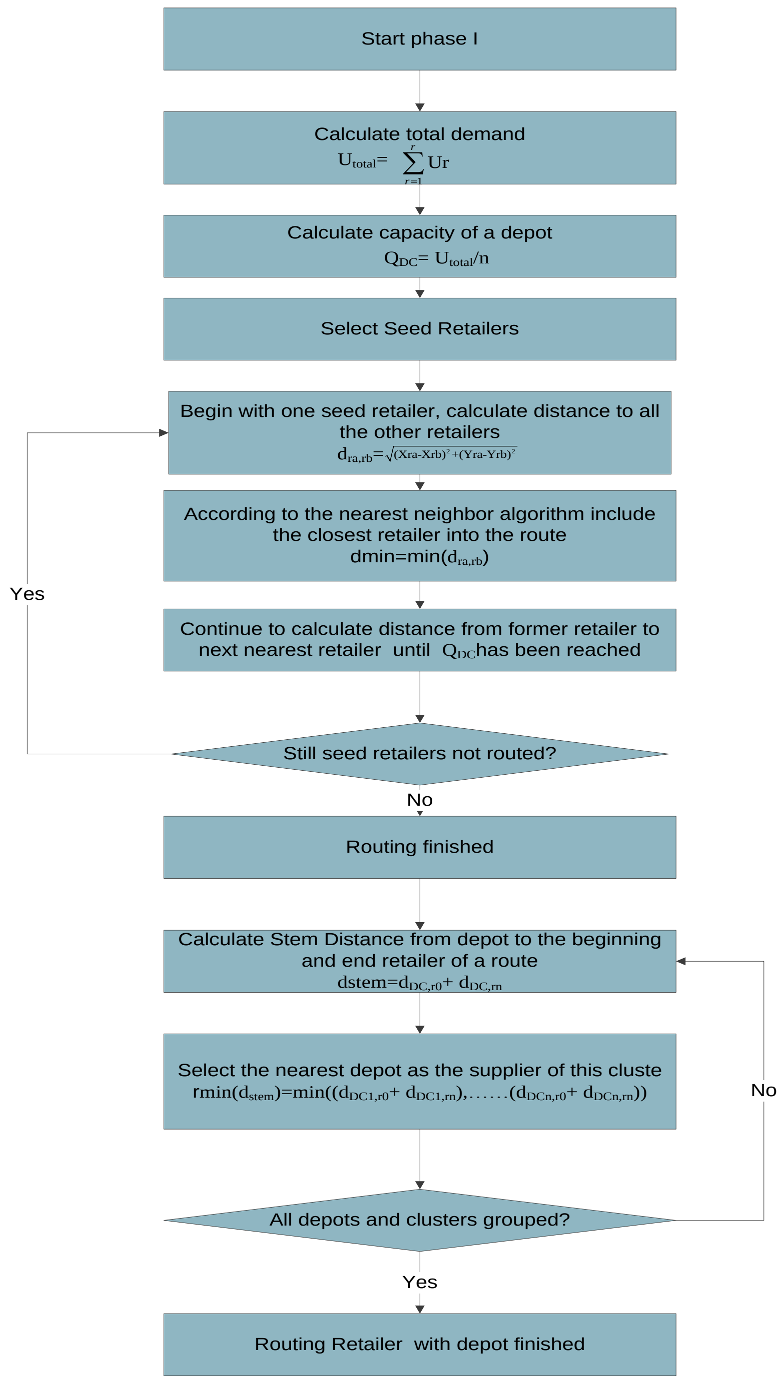


Figure 3.13: Flowchart for Phase I

STEP 2: Begin with a random retailer (r_o). In order to avoid missing remote points, we consciously chose those points as the start one, which are located far away from the depot.

STEP 3: Based on the nearest neighbor algorithm, route all the closer retailers into a single route by considering their travelling distance from one point to another point until reaching the capacity limit of one depot.

$d_{0,r\ min}=\min(\sqrt{(X_{r0}-X_{r1})^2+(Y_{r0}-Y_{r1})^2},\ldots\ldots\sqrt{(X_{r0}-X_{rn})^2+(Y_{r0}-Y_{rn})^2})$

$d_{0,r\ min}$: distance from the first point to its nearest one in the route.

STEP 4: Repeat step 2,3 until all retailers are routed.

STEP 5: Calculate summation distance from each depot to the first point and the last point of each route to get the minimum stem distance.

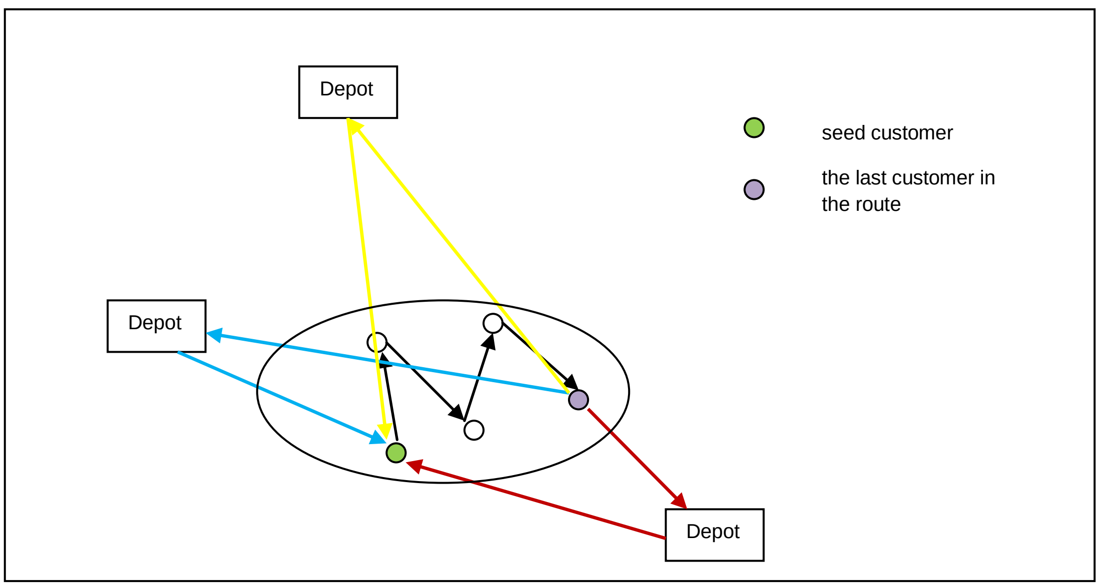


Figure 3.14:depot assignment

$\min(d_{stem})=\min((d_{DC1,r0}+d_{DC1,rn}),\ldots\ldots(d_{DCn,r0}+d_{DCn,rn})$

d_{stem}: total distance from the depot to the beginning and ending point of the route.

$d_{DC,r0}$: distance from the depot to the start point in a route

$d_{DC,rn}$: distance from the depot to the last point in a route.

STEP 6: Choose the closest depot as the central supplier of a customer group until each depot belongs to a separate cluster.

3.5.2 Phase II: Service Sequence List (SSL) generation

In this stage, the service sequence list, which takes an important role in phase III, is created based on the stock out time of retailers ordered according to the sequence from small to large.

The objective of this list is to sort the retailers according to the stockout time of different products.

3.5.3 Phase III: Route model

The customer service sequence list is partitioned by looking at the retailer's demands and the summation of demands less than or equal to vehicle capacity. Therefore, this model is made to give the minimum number of trips.

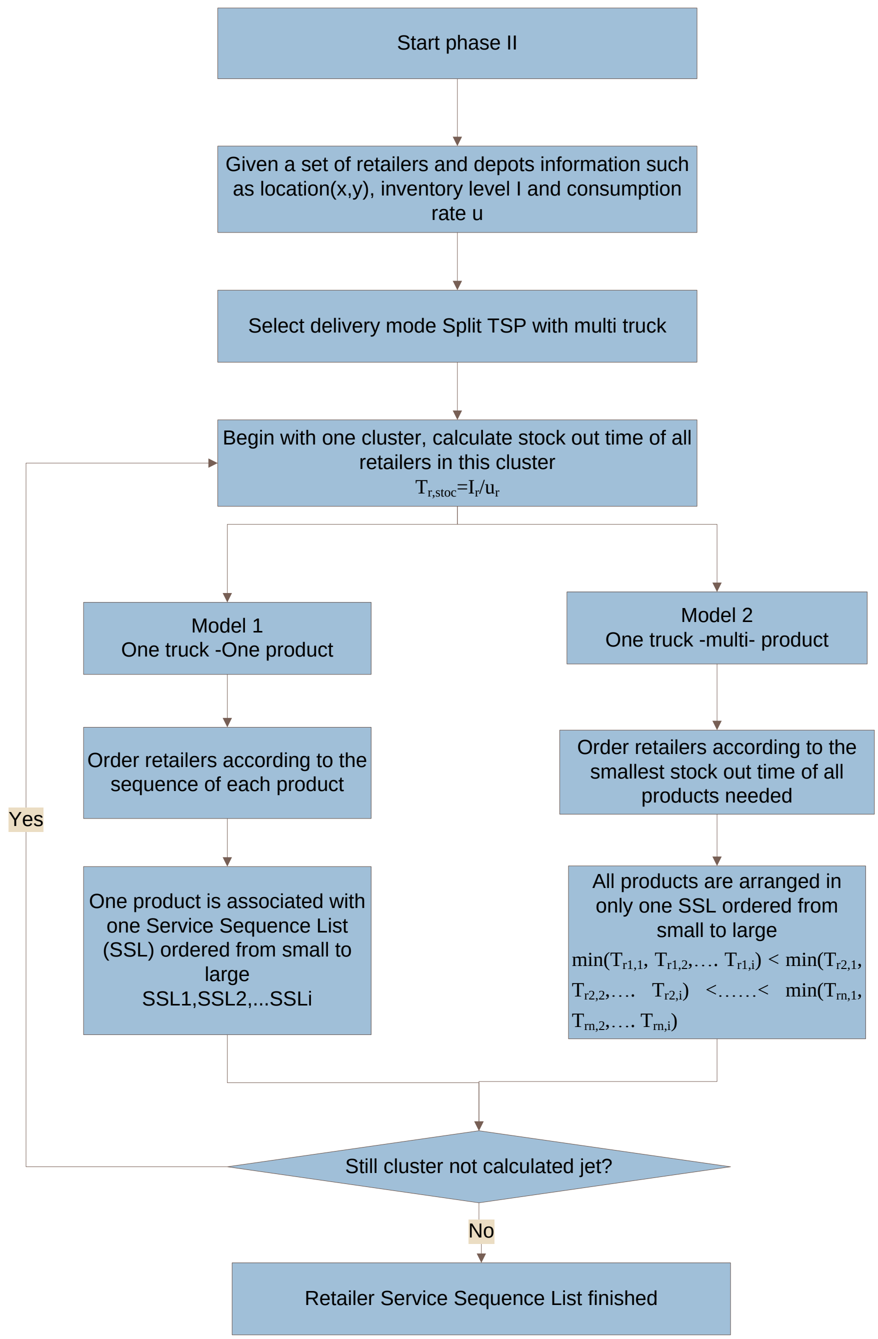


Figure 3.15: Flowchart for Phase II

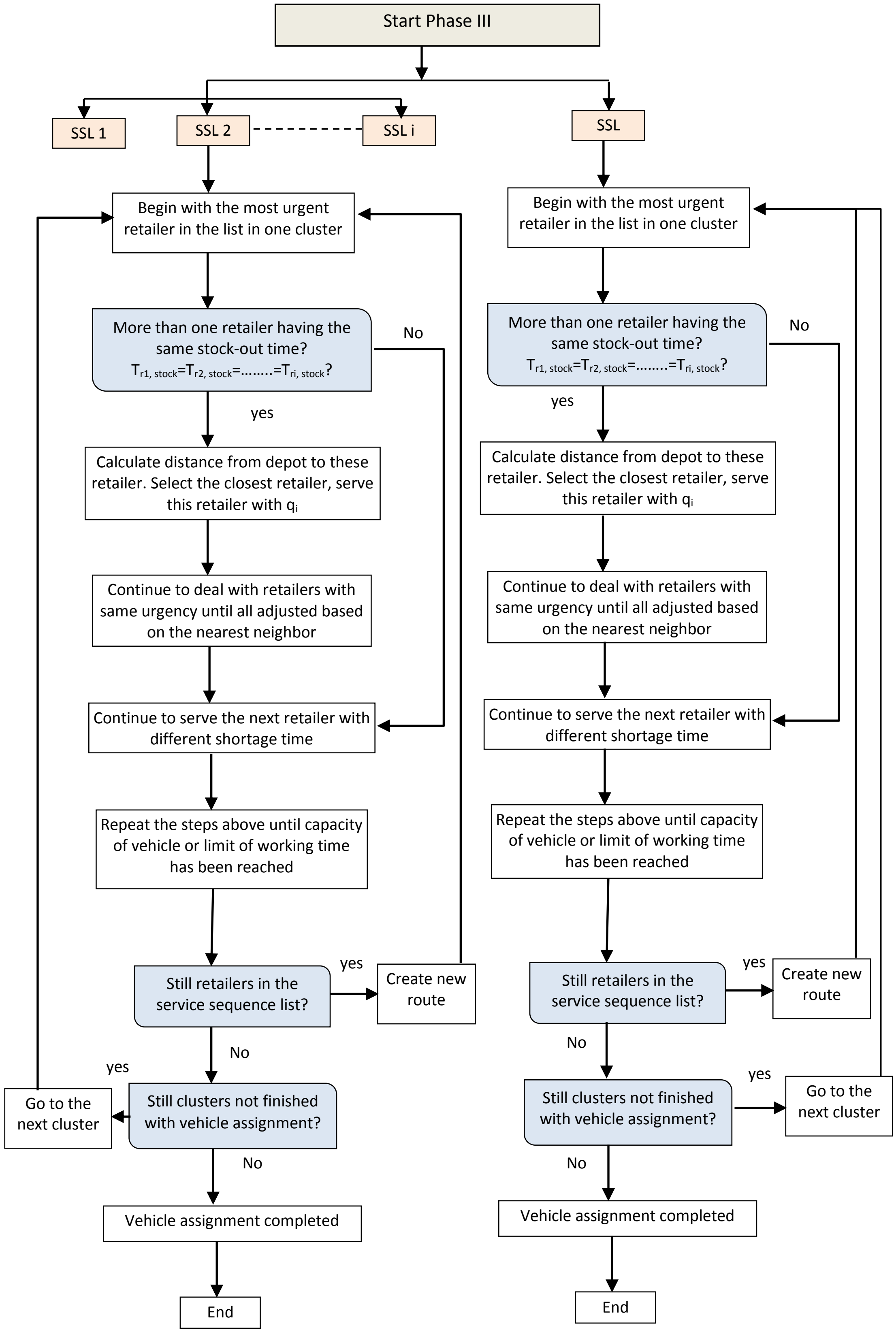


Figure 3.16: Flowchart for Phase III

4. Production, Inventory, and Transportation model

4.1 Introduction

The production, inventory and distribution routing system considered in this research consists of one production plant producing a multi products. The plant has limited production capacity and its own fleet for transportation. The manufactured products has to be delivered to retailers geographically dispersed on a grid to ensure fulfillment of the demand, which is considered deterministically known over a planning horizon. Delivery takes place by means of fleets of homogeneous transporters with same capacity.

Transportation costs of these fleets are proportional to the traveling distance instead of the shipped quantity. There is no fixed cost associated with transporter usage. It is assumed that each transporter can make multiple trips.

A supply chain environment with the following assumptions are considered:

- Multi products
- Single plant
- Multiple time periods within a planning horizon
- A heterogeneous fleet of transporter at the warehouse
- Each transporter can visit more than one customer during a trip, and can make multiple trips within one period if possible
- Each transporter returns to its base plant at the end of each period

As part of the solution methodology, this does not attempt to solve the full model but instead to investigate a relaxation referred to as the allocation model. In particular, the routing term in the objective function is replaced by a distribution component.

Figure 4.1 shows that block diagram of a multi-stage, multi-level production-inventory-distribution system. The details of the production inventory distribution system has been shown by this diagram.

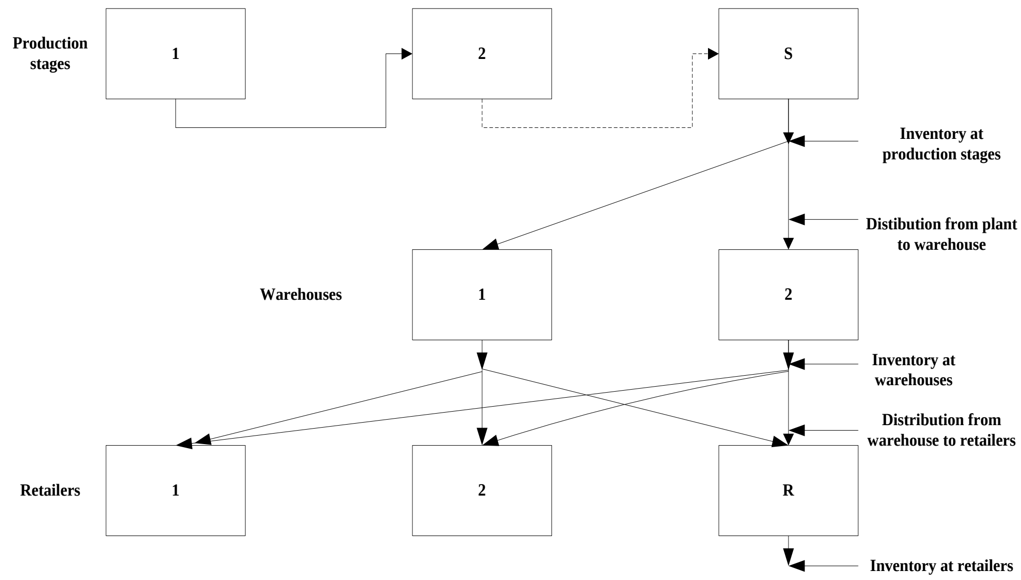


Figure 4.1 Block diagram of a multi-stage, multi-level production-inventory-distribution system[79]

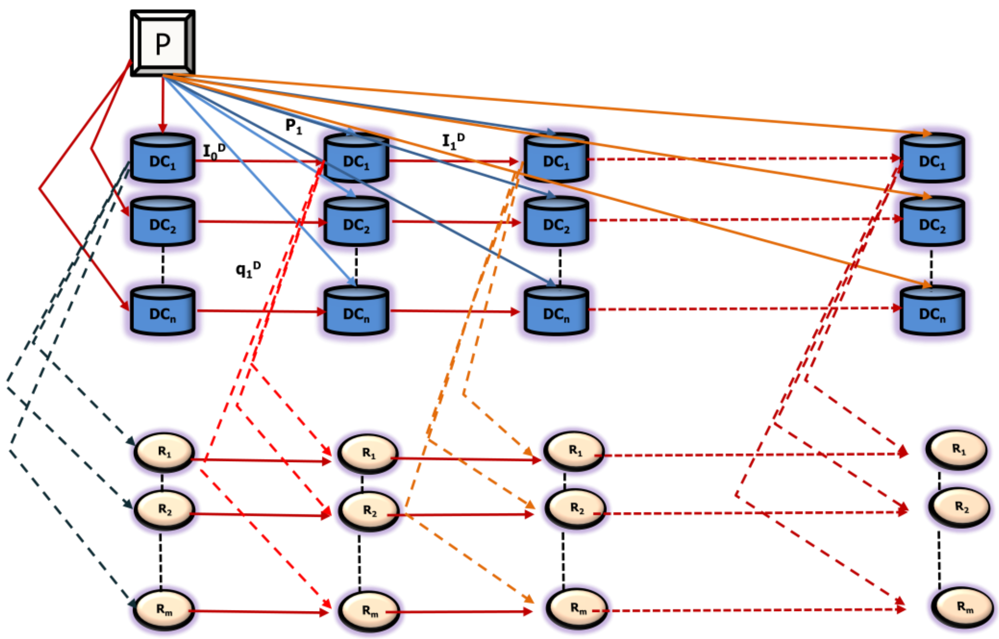


Figure 4.2 Production Inventory Distribution System

Figure 4.2 shows that there is a plant (which can produce multi products). These products delivered to warehouses, and from warehouses to the retailers. Also it shows the time horizon. The quantity available at the warehouse at the end of any day equals to the initial inventory at that day plus quantity received from the plant minus the quantity delivered to different retailers assigned to that warehouse.

4.2 Model Formulation

The problem is a single production facility which can produce multi products, and a set of retailers geographically dispersed on a grid. Each retailer r has a fixed nonnegative demand dirt in time period t of the planning horizon that must be satisfied, i.e., shortages are not permitted. A limited number of items can be produced in each time period and a limited number can be stored at a unit cost of Chip . In general, it is natural to equate a period with a day, which is done, but when production is scheduled for more than one shift in a day it could be to equate the period with one shift.

In constructing delivery schedules, each customer can be visited at most once per day and each of vehicles can make at most one trip per day. The latter restriction implies that all routes overlap in time. If c_v is the cost of going from warehouse w to retailer r and β_{rt} is a binary variable equal to 1 if retailer r is assigned by warehouse w, then the traveling costs is given cm in the full model. A limited amount of inventory can be stored at retailer r's at a unit cost of C_{hir}. Moreover, it is assumed that all deliveries take place at the beginning of the day and arrive in time to satisfy demand for at least that day. All production on day t is available for delivery only on the following morning and all inventories are measured at the end of the day. Demand on day *t* can be met from deliveries on day t and from ending inventory on day t−1 at the retailer. Initial customer inventory on day t simply reduces demand on subsequent days, while initial inventory at the plant must be routed; at the end of the planning horizon all inventory levels are required to be zero. The goal is to construct a production plan and delivery schedule that minimizes the sum of all costs while ensuring that each customer's demand is met over the planning horizon. In so doing, three critical decisions have to be made:

- How many items to manufacture each day,
- How much to deliver to a customer during each visit,
- Which delivery routes to use.

The Figure 4.3 shows that block diagram of a multi-stage, multi-level production-inventory-distribution system. The details of the production inventory distribution system has been shown by this diagram.

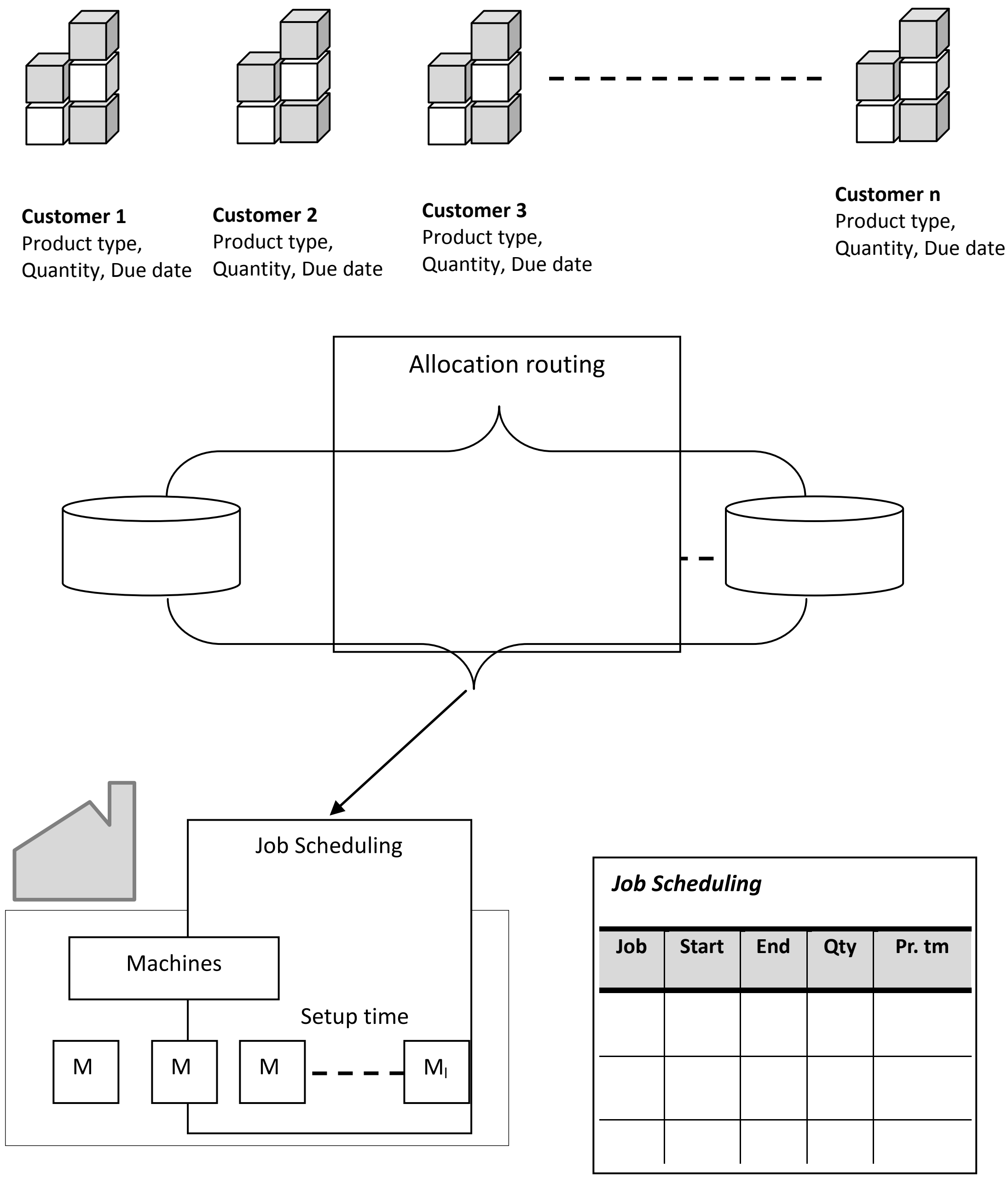


Figure 4.3 Block diagram of a multi-stage, multi-level production-inventory-distribution system

Notations

Symbol	Definition
S	Number of production stages
F_{st}	Fixed or setup cost at stage s in period t
Y_{st}	(0,1) variable, equal to 0 when there is no setup at stage s in period t
X_{st}	Quantity produced at stage s in period t
m	distribution cycle (t=1,2,3……m)
T	distribution cycle time (one week)
P	plant
l	distribution center ($d=d_1,d_{2,\ldots\ldots}d_l$)
n	retailers (r=1,2,3…..n)
N	product (i=1,2….N)
d_{irt}	demand of retailer r for product i at time t
I_{irt}	inventory level of retailer r for product i
I_{idt}	inventory level of the depot for product i
I_{ipt}	inventory level of the plant for product i
q_{irt}	quantity of product i distributed from depot to retailer r
q_{idt}	replenished quantity of product i from plant to depot
q_{ipt}	produced quantitiy of product i at plant
α_{dt}	1 or 0, when $q_{idt}>0$ or otherwise
β_{rt}	1 or 0, when $q_{irt}>0$ or otherwise
C_{hip}	unit inventory holding cost for product i at plant
C_{hid}	unit inventory holding cost for product i at depot

C_{hir}	unit inventory holding cost for product i at retailer
d_{xy}	total distance for route y which belongs to depot d (x=1,2……n, y=1,2……n)
d_{pd}	distance between plant and depots (d= $d_1, d_2, \ldots d_l$)
C_v	variable transportation cost in unit distance

Variable definitions for the IRP model

Symbol	**Definition**
C_{Thp}	total holding cost for plant
C_{Thd}	total holding cost for depot
C_{TTd}	total transportation cost for depot
C_{Thr}	total holding cost for retailer
C_{TTr}	total transportation cost for retailer

The integrated production, inventory and distribution routing problem can then be formulated as follows:

minimizing total cost = min (setup cost+ inventory cost of all products at the plant + Inventory cost at DC's + transportation cost from the plant to DC's + inventory cost at retailers + transportation cost from DC's to retailers).

$$\min \quad \sum_{t=1}^{m}\sum_{s=1}^{S} F_{st}Y_{st} + \sum_{t=1}^{m}\sum_{i=1}^{N} C_{hip}\frac{I_{ipt-1}+I_{ipt}}{2} + \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{d=1}^{l} C_{hid}\frac{I_{idt-1}+I_{idt}}{2} + \sum_{t=1}^{m}\sum_{d=1}^{l} 2C_v d_{pd}\alpha_{dt} + \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{r=1}^{n} C_{hir}\frac{I_{irt-1}+I_{irt}}{2} + \sum_{t=1}^{m}\sum_{x=1}^{d}\sum_{y=1}^{n} C_v d_{xy}\beta_{rt} \tag{4.1}$$

s.t.

$$X_{st} \leq \text{total capacity of the plant}, \quad \forall\, s, t \tag{4.2}$$

Total holding cost for plant:

$$C_{Thp}= \sum_{t=1}^{m}\sum_{i=1}^{N} C_{hip} \frac{Iipt\text{-}1+Iipt}{2} \tag{4.3}$$

$$I_{ipt}=I_{ipt-1} + q_{ipt} - \sum_{d=1}^{l} q_{idt} \quad \forall\, i, t , i\in N, t\in T \; p=1 \tag{4.4}$$

Total holding cost for depot:

$$C_{Thd}= \sum_{t=1}^{m}\sum_{i=1}^{N} C_{hid} \frac{Iidt\text{-}1+Iidt}{2} \tag{4.5}$$

$$I_{idt}=I_{idt-1} + q_{idt} - \sum_{r=1}^{n} q_{irt} \quad \forall\, i, t, i\in N, t\in T \tag{4.6}$$

Total transportation cost for depot

$$C_{TTd} = \sum_{i=1}^{m}\sum_{d=1}^{l} 2C_v d_{pd}\alpha_{it} , \; \alpha_{it} \in \{0,1\} \quad \forall\, i, t, i\in N, t\in T \tag{4.7}$$

Total holding cost for retailer

$$C_{Thr}= \sum_{t=1}^{m}\sum_{i=1}^{N}\sum_{r=1}^{n} C_{hir} \frac{Iirt\text{-}1+Iirt}{2} \tag{4.8}$$

$$I_{irt} = I_{irt-1}+ q_{irt} - d_{irt} \quad \forall\, i, t, \; \forall\, i, t, i\in N, t\in T, r\in n \tag{4.9}$$

Total transportation cost for retailer

$$C_{TTr}= \sum_{t=1}^{m}\sum_{x=0}^{n}\sum_{y=0}^{n} C_v d_{xy}\beta_{rt} , \; \beta_{rt} \in \{0,1\} \quad \forall\, t, t\in T, r\in n \tag{4.10}$$

Storage capacity and safety stock requirement constraints

$$0 \le I_{ipt} \le I_p^{max} \quad \forall\, i, t, i\in N, t\in T \tag{4.11}$$

$$0 \le I_{idt} \le I_d^{max} \quad \forall\, i, t, i\in N, t\in T \tag{4.12}$$

$0 \leq I_{irt} \leq I_r^{max} \quad \forall$ i, t, i∈N, t∈T (4.13)

Non-negative and integer requirement

$q_{irt} \geq 0$ $q_{idt} \geq 0$ $q_{ipt} \geq 0$ $\forall$ i, t, i∈N, t∈T (4.14)

The objective function minimizes the sum of production setup costs, a surrogate for the routing costs, holding costs at the plant, and holding costs at the retailers.

Constraint (4.2) ensures that the total production capacity at each stage should not exceed the plant production capacity. Constraints (4.3) and (4.4) assure the balance at the plant among production, inventory and delivery, and the demand fulfillment for depot respectively. Constraint (4.3) is the average inventory level at plant. Constraint (4.4) is the inventory balance constraint at plant, which requires that distribution from the plant can be met from inventory and current production in that period. Constraints (4.5) and (4.6) assure the balance at the depot among replenishment, inventory and delivery, and the demand fulfillment for retailers respectively. Constraint (4.5) is the average inventory level at depot. Constraint (4.6) is the inventory balance constraint at depot, which requires that distribution from the depot can be met from inventory and replenishment from plant in that period. Constrain (4.7) is the transportation cost for depot including variable cost when one delivery is placed from plant to depot. Constraints (4.8) and (4.9) assure the balance at the retailer among replenishment, inventory and delivery, and the demand fulfillment for customers respectively. Constraint (4.8) is the average inventory level at retailers. Constraint (4.9) is the inventory balance constraint at retailers, which requires that demand from customers will be met from inventory and replenishment from depot in that period. Constrain (4.10) is the transportation cost for retailers including variable cost when one replenishment is placed from depot to retailers. Constraints (4.11), (4.12) and (4.13) are inventory constraints satisfying maximum storage capacity and inventory requirements at plant, depots and retailers. And finally, constraint (4.14) is non-negative constraints.

4.3 Heuristic Algorithm for PIDP

The production distribution model suggested by Milind et al.[69] was developed. They considered a data set which included two products delivered to six retailers. One truck with limited capacity was used to deliver the products in their model. They used a full truck load model.

Figure (4.4) shows the suggested solution to solve this problem.

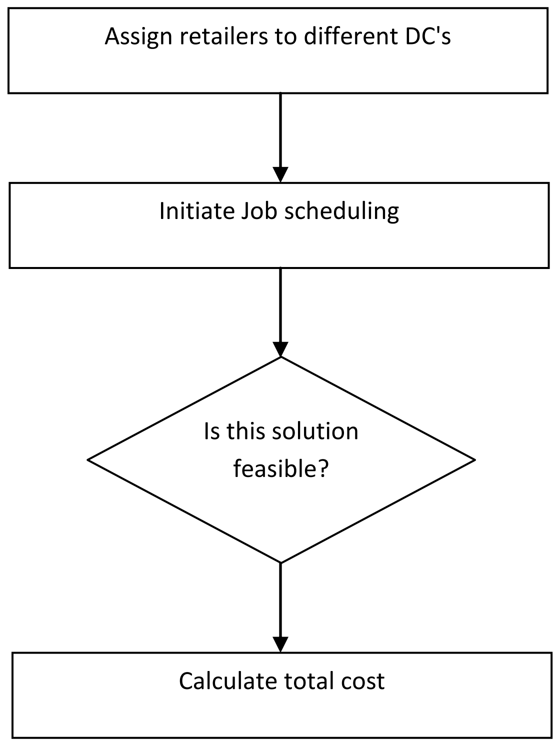


Figure (4.4) The general view of the suggested algorithm.

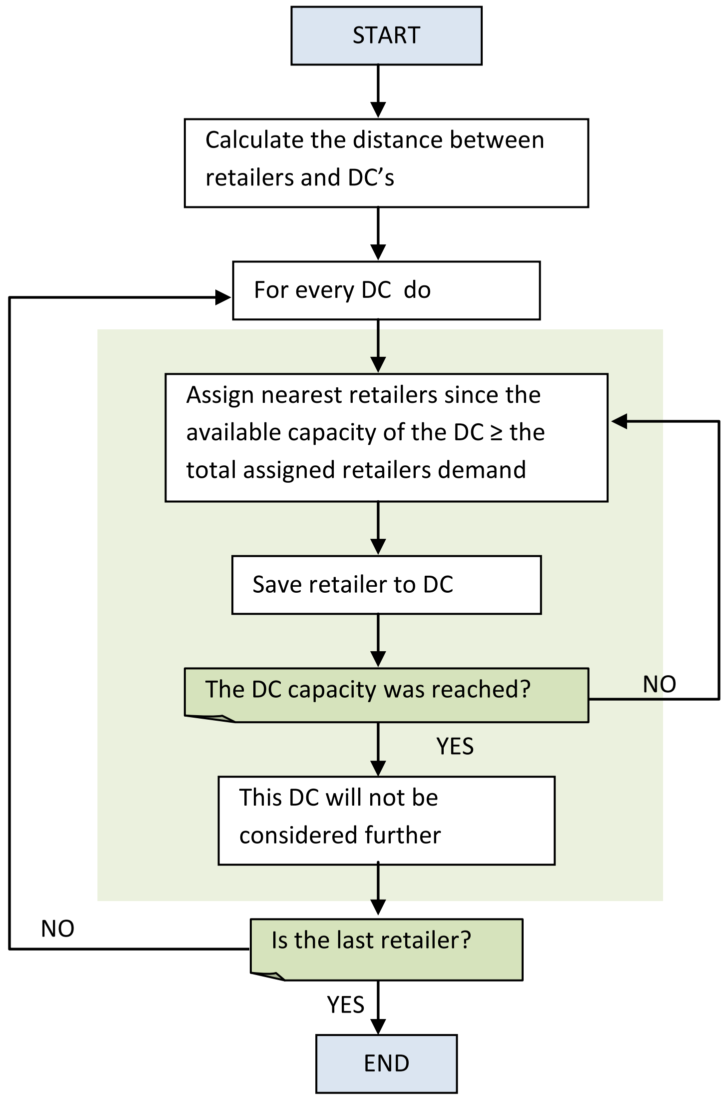


Figure (4.5): Allocation problem

The algorithm suggested is as follows:

Step 1: Finding the initial schedule

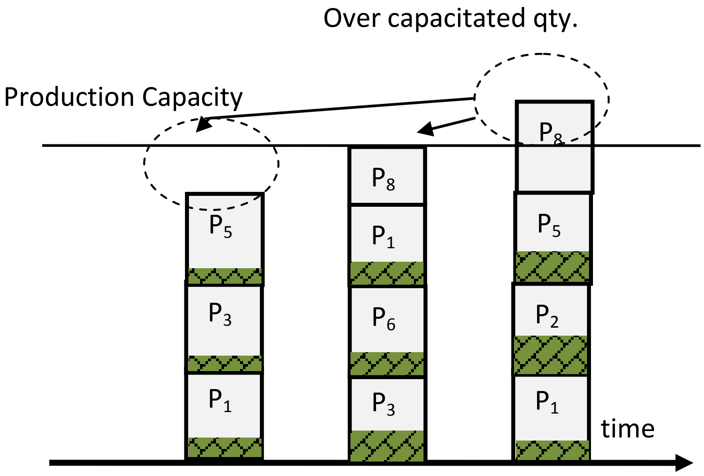
Construct an Earliest Due Date (EDD) schedule according to the non decreasing order of the due dates and minimizing the total.

If there is more than one order in the same day, schedule these orders to minimize the setup cost.

Step 2: Feasibility check

Starting from the last time period, if period t is over capacitated, choose the order that minimizes the setup time and shift it to the period t-1. If period t-1 not capacitated rearrange the orders of this period considering the added quantity. Otherwise, shift the over capacitated to the previous day. Repeat this step till the first period.

Figure (4.6) shows this concept.



This figure shows that there is over capacitated quantity in the last period. Checking the previous period shows that it can't be shifted to that period.

Figure (4.6): the algorithm concept

3. Step 3: construct daily VRP scheduling plan.

4.4 SimAL software

The advanced planning and scheduling system SimAL was used to solve the scheduling problem. Using SimAL provides an opportunity to use the suggested algorithm to solve different models of job scheduling. SimAL[93] is a comprehensive planning solution used to strengthen the competitiveness of the enterprise. SimAL guarantees the observance of delivery and reduction of stocks while sustainably increasing the productivity and efficiency of the business.

SimAL increases flexibility as planning and production are linked in real time and the exchange of information is automated and accelerated. The integration is carried out both with the ERP system as well as the production software or manufacturing automation solutions. This means that all production-related data are practically available in real time.

Through the use of advanced simulation and optimization processes in SimAL, planning can also be automated. This not only increases the quality of the design but also enhances business responsiveness by short-term rescheduling and thus contributes to lowering the total cost of ownership. The timeliness and completeness of all production-related data with SimAL also enables an effective controlling of production performance.

Controlling the production scheduler provides the necessary transparency and supplemental measures to increase the efficiency of production on the one hand and to optimize the long-term strategic planning on the other.

SimAL is an advanced planning, scheduling and information system that can be employed irrespective of the type of production or particular branch of industry. Its control system stands for a comprehensive solution for optimizing the manufacturing resource planning (MRP II) and can be also put to good use as scheduling control system even where there is no functioning MRP II system. Graphical planning panel for user-friendly scheduling, display of order status and completion-date and resource conflicts is the feature of SimAL. Additionally, groups of planners can work in parallel thanks to system networking. Results and conflicts are displayed to all planning groups involved administration to all resources: personnel, tools, store, buffer zones etc.

It is known that, each production process is unique and this must also be reflected in software. On the one hand, it is sensible to use standard products for using their powerful functionality and not have to constantly reinvent the wheel; but on the other hand, software that caters to exact restrictions of the production process to be scheduled is indispensable. So in order to balance these two conditions, we need a data dictionary in SimAL. While setting up an object in SimAL, we must to be sure a relative Data Dictionary for the object is available. In this Data Dictionary, all basic object types (such as the ERP order, disposition order and so on) as well as the attributes available in the types are predefined, then we can start edit the characters for the required machine, resource and other data for the project.

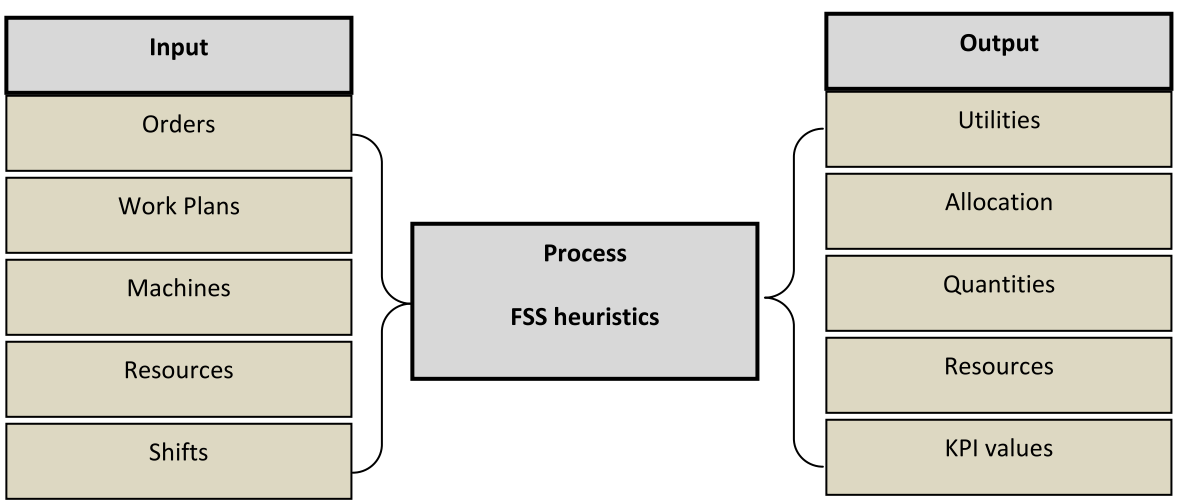


Figure 4.7: Some important Inputs and Outputs in SimAL

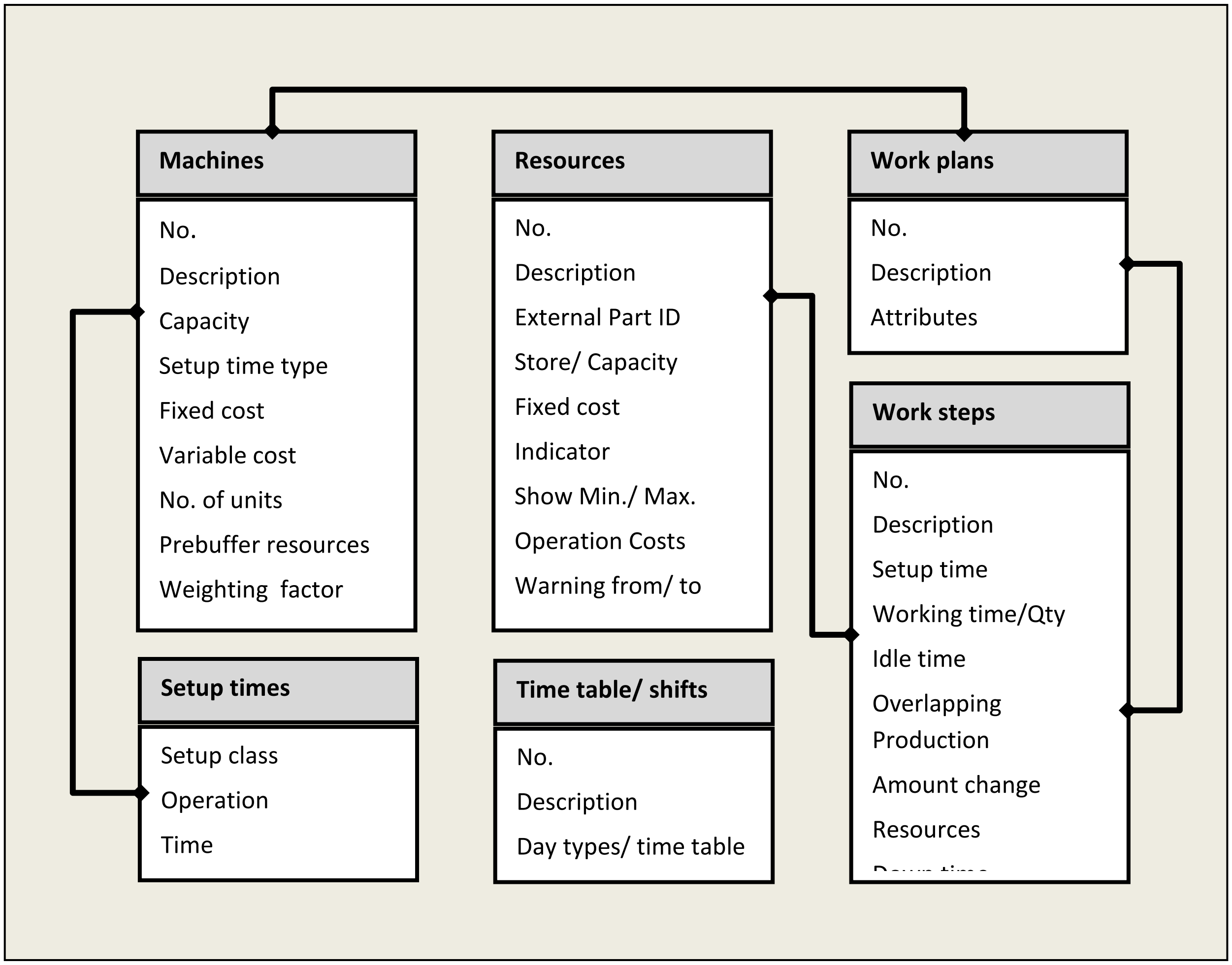


Fig. 4.8 Inputs of SimAl

In the following some important inputs to the software are explained.

Every machine to be scheduled has to be registered with SimAL. The list of machine edition is not only shows all machines currently documented, but also offers a wide option of editing possibilities to parameterize and manage the machines. Figure 4.9 shows all the machines that are used in this case study.

Figure 4.9 shows, there are 6 machines that are registered with SimAL.

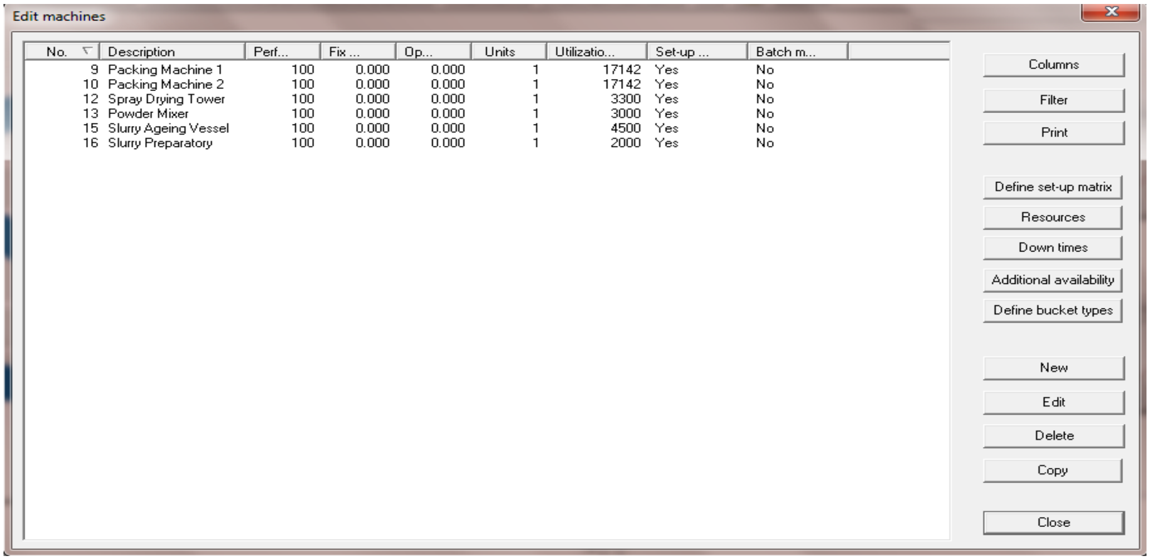


Figure 4.9: List of machines

To edit the machines that is listed above, the machine has to be chosen that has to be edited, and then click on the button Edit that is on the right side of the screen.

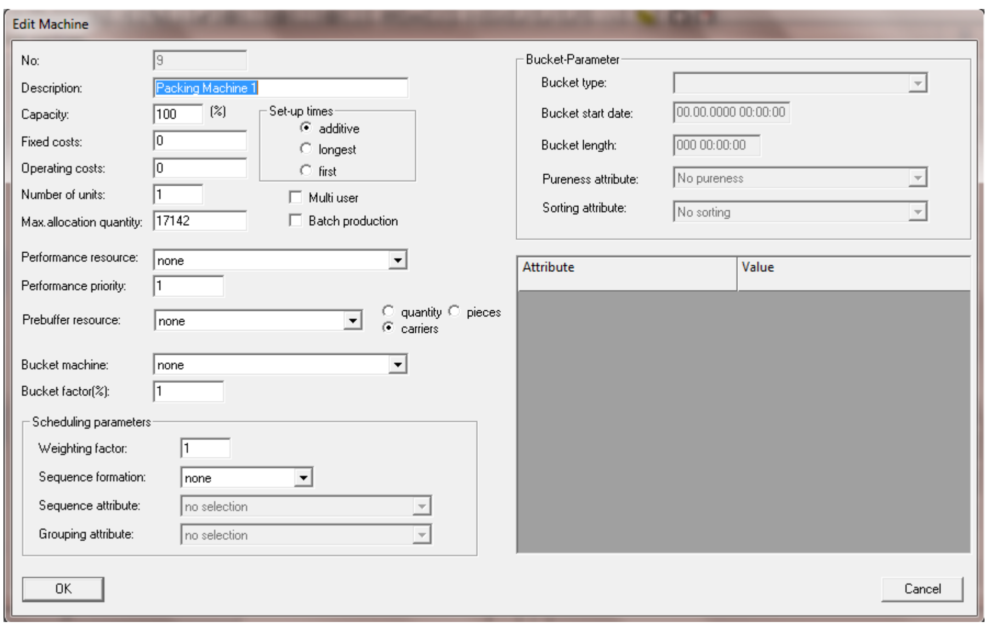


Figure 4.10: Editing machine

All units which are needed additionally for a scheduled machine for finishing of a part are called resources. A resource could be a worker (with a particular qualification), a tool, electricity or water, for example.

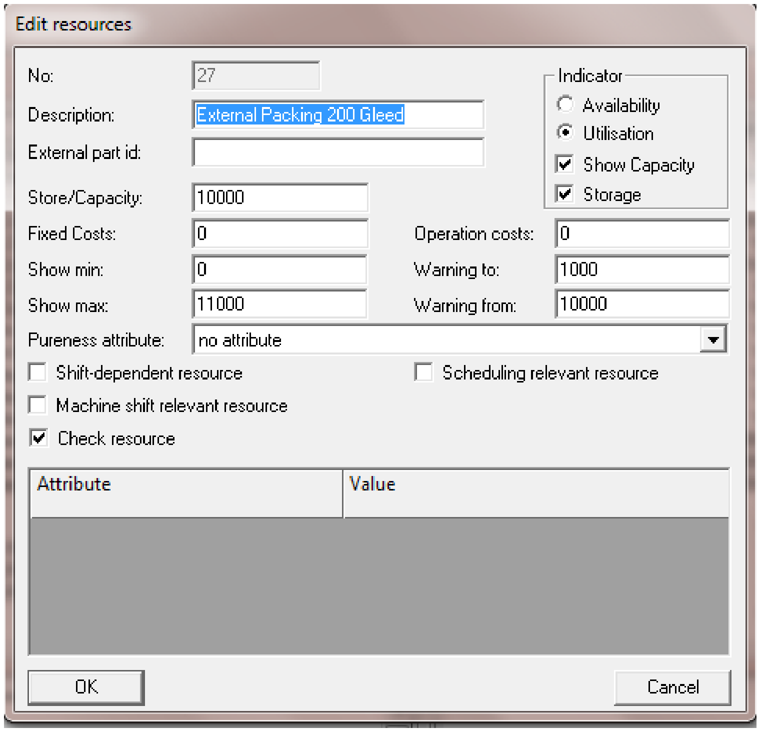


Figure 4.11: Setting up/editing resources

Figure 4.11 shows the information of resource the detergent Gleed 200 gm for the external packing. The list in the figure 4.10 shows the »Stock/Capacity« is 10000. It means, there can be 10000 cartons of the detergent Gleed be stored.

The production process is illustrated with the help of production graphs and work plans in SimAL. Work plans illustrate linear production sequences with process alternatives. With the help of production graphs, several work plans can be chained together in nearly any structure. Work plans, on the other hand, consist of one or more processes. After selecting the menu entry, an overview box consisting of two parts is opened Figure 4.12 the left window shows all the currently set-up work plans while the right window lists the processes which belong to the chosen work plan.

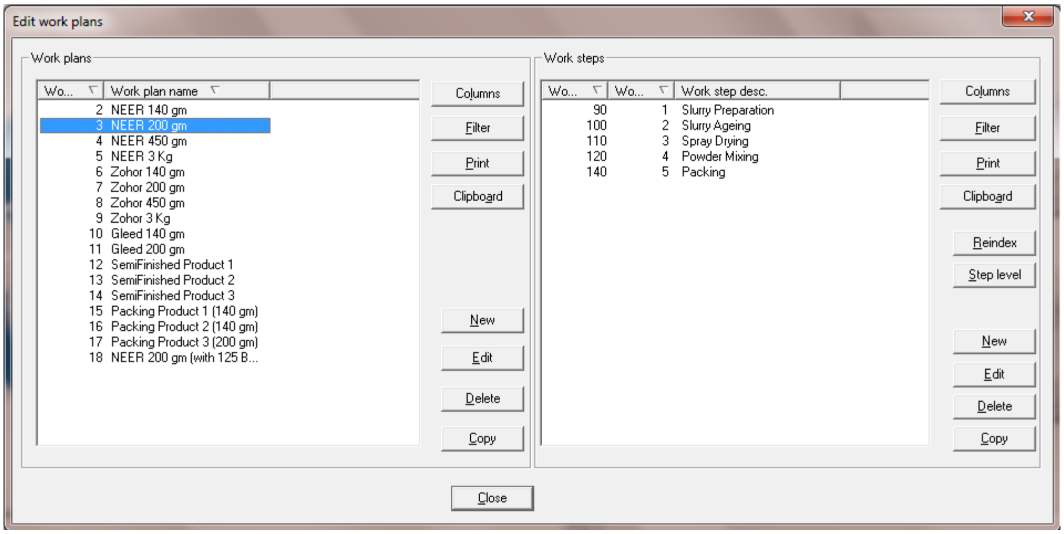


Figure 4.12: Overview box of work plans

Figure below (4.13) shows the work step Packing of work plan of Neer 200 gm.

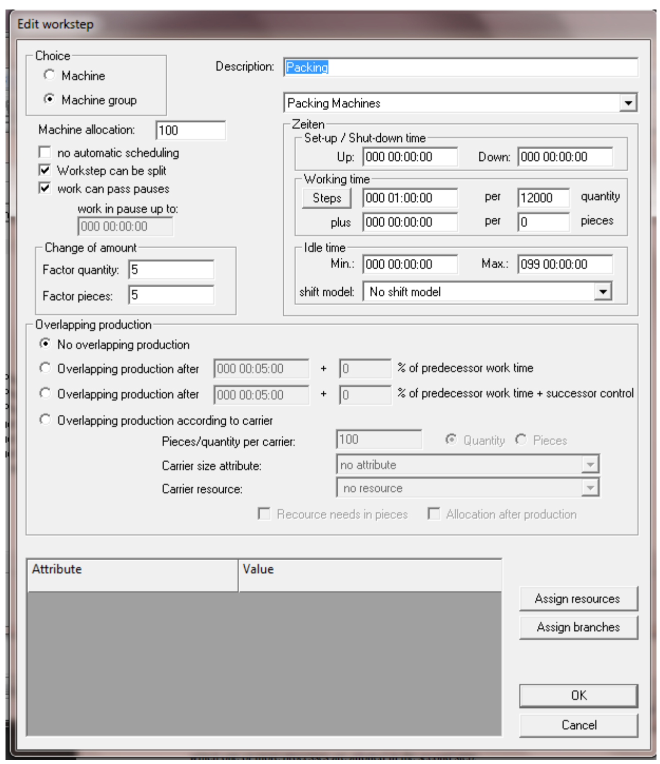


Figure 4.13: Editing a process

A fixed set-up time, which accumulates at the beginning of the process, can be parameterized in the box »Set-up time«. The necessary processing time with respect to the work factor " per quantity" or " per piece" is defined in the box »Processing time«. For the work step packaging the working time for 12000 quantities is 1 hour.

The checkboxes »Factor Quantity« and »Factor Piece« help in describing how a process affects the quantity and number of pieces of the orders.
Managing of shifts by SimAL offers the highest flexibility without needing complicated entries from the user. The main aspect here is defining all necessary shift schedules in four steps, which are based on each other and which can be supplemented or extended at any time (Figure 4.14).

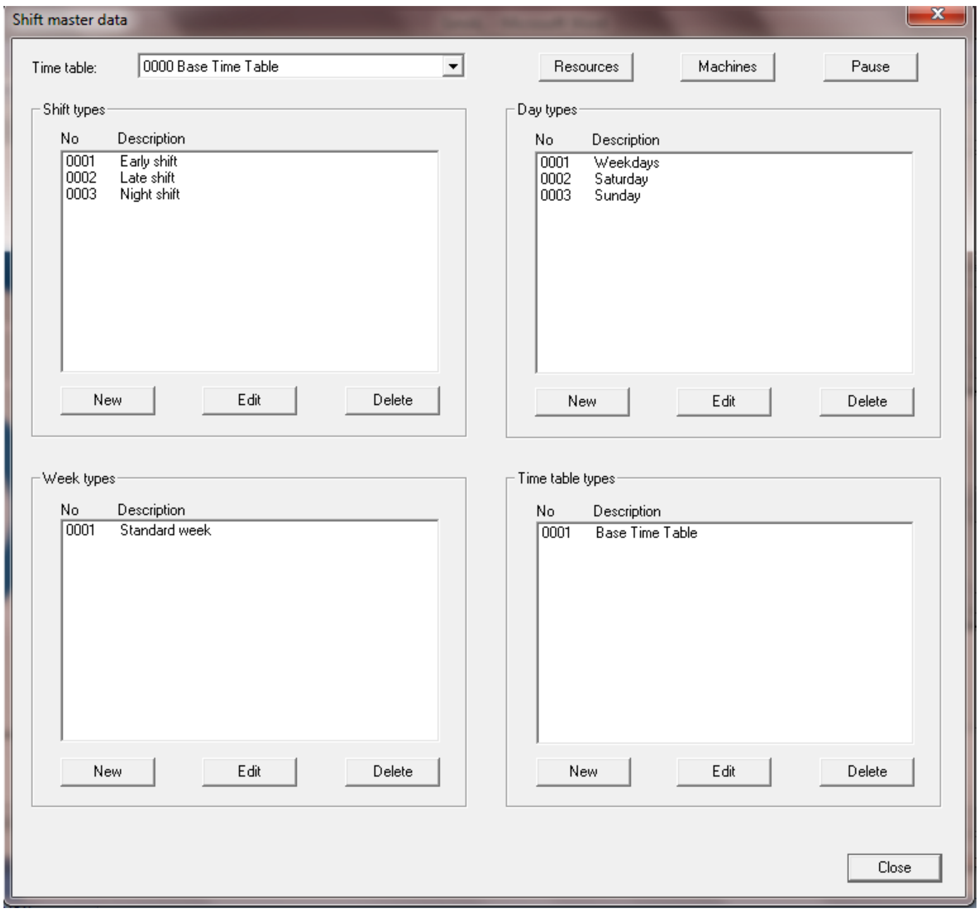


Fig4.14: Overview of shifts to be edited

In the menu entry ERP INTERFACE, all the functions to manipulate ERP orders can be found. This includes editing, accepting and deleting of ERP orders as well as functions for communication of SimAL with connected Enterprise Resource Planning Systems (ERP) and Production Data Acquisition (PDA) systems.

Figure shows ERP Order 2 of Detergent production. From the edition menu we can enter the basic characters of the ERP order, such as the due time, the required quantity, the material information, priority and so on. Before the process of a ERP order can be scheduled in the schedule window, they first have to be generated into the schedule window.

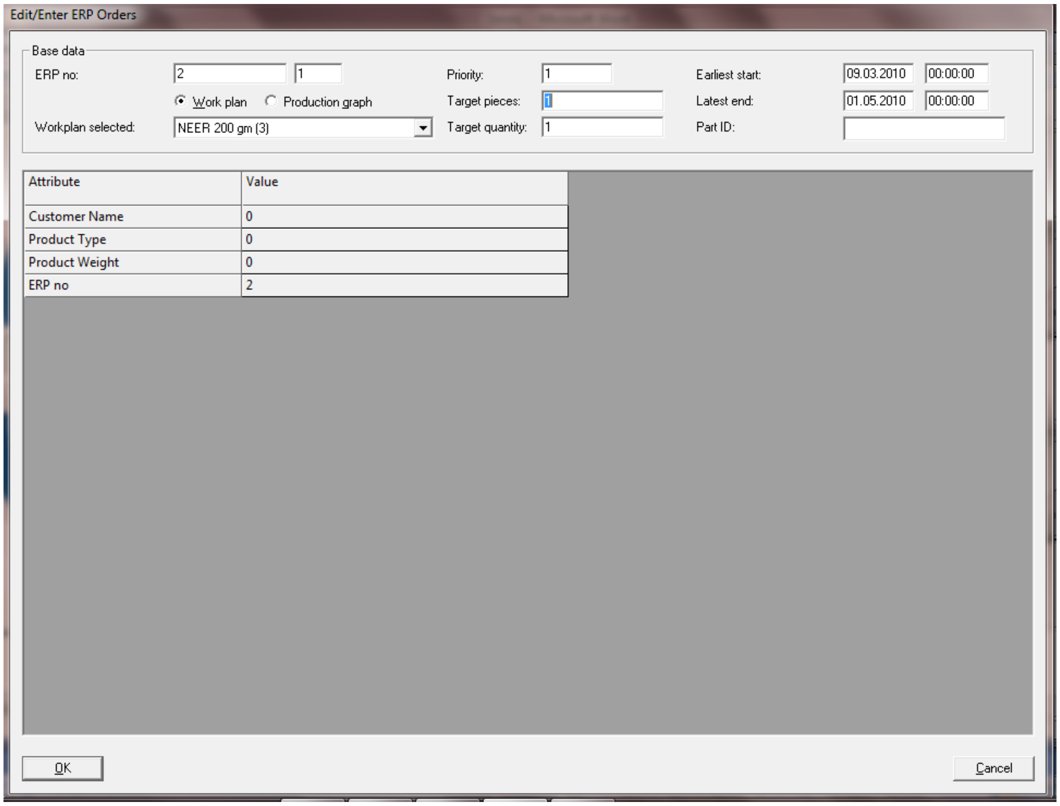


Figure 4.15: Editing ERP orders

Figure (4.16) shows the main result screen in the software

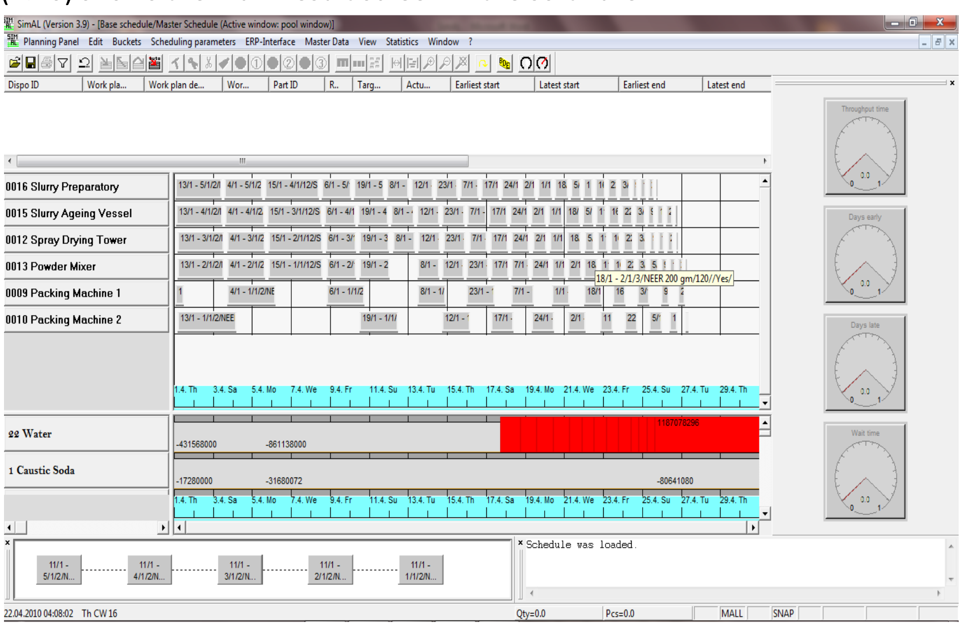


Figure (4.16) Main result screen

Figure (4.17) shows one of the statistics screens

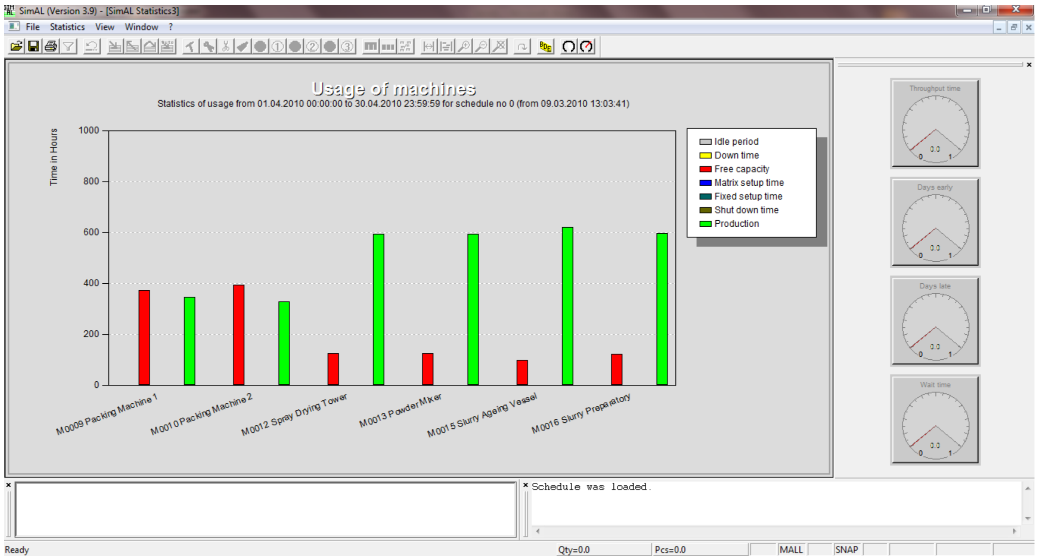


Figure (4.17) One of the statistics screen

5. LOCATION ROUTING PROBLEM

The Multi-Depot Location Routing Problem occurs in the physical distribution system's design. An important element in the design of a physical distribution system is the location of depots, and the distribution of goods from depot to customer occurs in a straight to and back manner while computing distribution costs. This is true only if the delivery to each customer is a truckload, but for deliveries that are less than a truckload (LTL) multiple customers are served on a single route. Thus the true distribution costs are the route costs for all customers. Several unrealistic assumptions, such as homogeneous fleet type and unlimited number of available vehicles, are typically made concerning this problem, and since the inherent complexity of the MDLRP problem makes it impossible to solve the problem on a larger scale, the original problem is divided into two sub-problems, i.e., the location-allocation problem, and the general vehicle routing problem, respectively. Each sub-problem is then solved in a sequential and iterative manner by a certain algorithm embedded in the general framework for the problem-solving procedure. This chapter considers the analysis of some algorithms for the Multi-Depot Location Routing Problem (MDLRP) and the development of a decision-making tool on the basis of these algorithms with a visual basic programming language. In addition, the setting of parameters throughout the solution procedure for obtaining quick and favourable solutions is also suggested.

Over the past few decades, the concept of integrated logistics systems has emerged as a new management philosophy which aims to increase distribution efficiency. Such a concept recognizes the interdependence among the location of facilities, the allocation of suppliers and customers to the facilities, and the vehicle route structure around depots or distribution center (DC). As such, it coordinates a broader spectrum of location and routing options available to logistics managers and consequently avoids the sub-optimization of distribution solutions. Since finding the optimal solution for this problem is a non-polynomial problem, several heuristics for searching local optima have been proposed. In this chapter the ADD and DROP algorithms will be explained, and a software tool has been developed to solve this problem.

The distribution center location problem is basically one of finding the optimal balance between transportation and warehousing costs. The cost of transportation is often the most significant cost component in a distribution system. In most cases, an increase in the number of distribution centers would result in higher warehousing costs and lower transportation costs. Analytic models for distribution center location represent warehousing costs as the sum of fixed costs (construction and maintenance of buildings and roads) and variable costs (labor, material handling equipment, order processing). Transportation costs include the cost of shipping from the supply sources (plants) to the distribution centers (trucking cost) and the cost of shipping from the distribution centers to customers (delivery cost).

In practice, there are two main ways of distributing products from facilities to customers. (1) Each delivery vehicle serves only one customer on a straight-and-back basis on a given route. This is the case when the customer demand is a full truckload (TL). (2) A vehicle stops at more than one customer on its route, which is the case if each customer's requirement is less than a truckload (LTL). For the first case, it is appropriate to assume that the delivery cost can be represented by the moment sum cost function where the unit shipment cost from a facility to a customer is assumed to be independent of the route taken to visit the customer. Then the total delivery cost is the sum, overall customers and facilities, of the production. But most cases in practice are of the second type, for which the transportation cost is hard to estimate.

In order to get an efficient and cost-effective decision for strategic location allocation and corresponding daily operation in a supply chain, different computer-programmed tools were developed. These tools were basically developed from several popular heuristic algorithms: such as nearest neighbour for the routing algorithm and shortest stem distance for the location allocation method. After the initial results, some other methods were also implemented to improve the route and assignment of depots.

The aim of this part is to try to minimize the total cost by finding the optimum location for the distribution centers.

Liu and Lee[59] composed the following definition of MDLRP from several literatures: “determining locations of depots from several candidates and finding the optimal set of vehicle schedules and routes based on the shortest travelling distance criteria.” MDLRP could be categorised into two sub-problems: a location allocation problem (LAP) and a vehicle routing problem (VRP)[106].

Daskin[15] pointed out that there were interrelated decisions involved in the LRP.

These decisions include: (i) How many facilities are to be located? (ii) Where should the facilities be? (iii) Which customers are to be assigned to which warehouses? (iv) In what order should customers be served on each route? The LRP is categorised as NP-hard problems.

Table 5.1. Classification of LRP with regard to its problem perspective[52].

Network levels	Single stage / Two stages
Demand / Supply	Deterministic / Stochastic
Number of facilities	Single facility / Multiple facilities
Size of vehicle fleets	Single vehicle / Multiple vehicles
Vehicle capacity	Uncapacitated / Capacitated
Facility capacity	Uncapacitated / Capacitated
Facility layer	Primary / Secondary / Intermediate
Planning horizon	Single period (static) / Multiple periods (dynamic)
Time windows	Unspecified time with no deadline Soft time windows with loose deadlines Hard time windows with strict deadlines
Objective function	Single objective / Multiple objectives
Types of model data	Hypothetical / Real-world

The proposed methodology is based on the ADD-heuristic and DROP-heuristic solution for the location and allocation problem (LAP) and the savings algorithm for the vehicle routing problem (VRP).

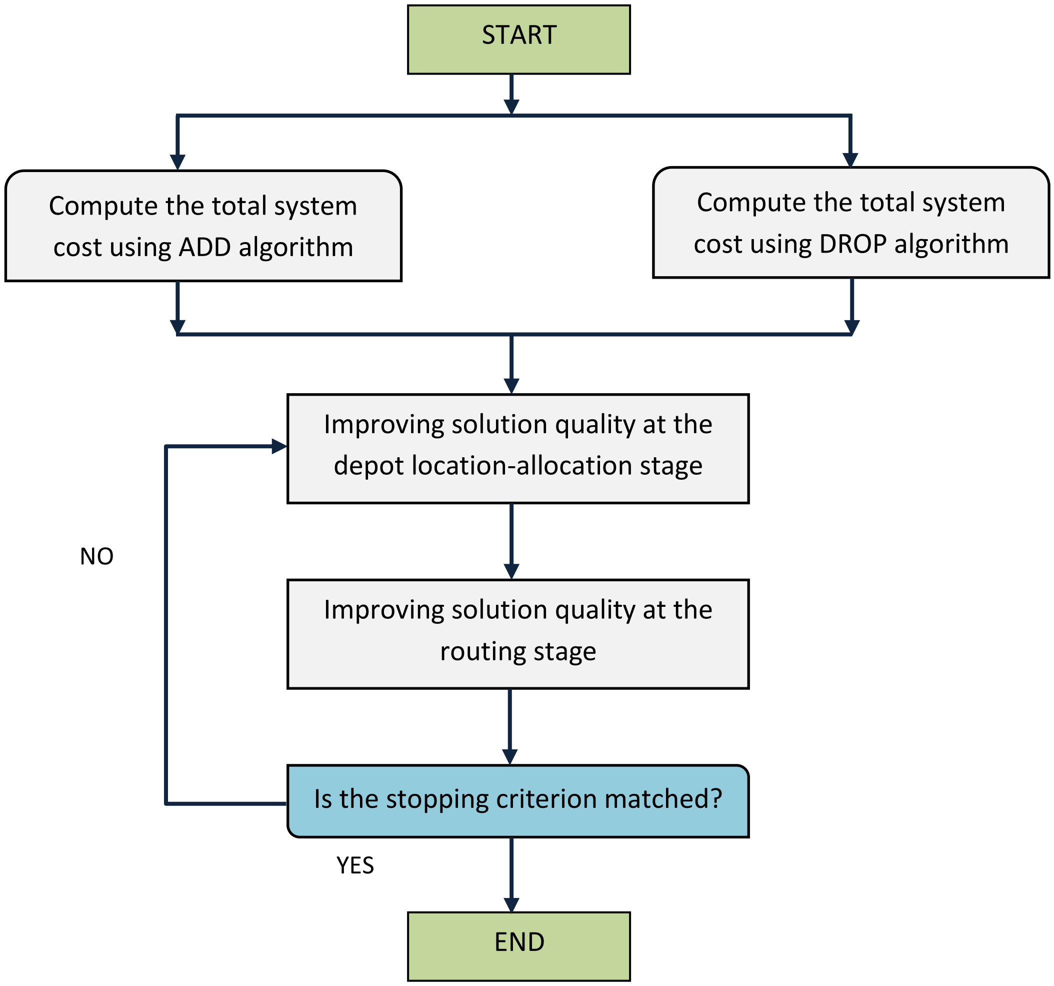


Figure 5. 1 The flowchart for solution methodology

5.1. HEURISTIC FOR LOCATION AND ALLOCATION PROBLEM

The solution of the LRP algorithm that leads to an optimal result is known as the exact solution (for example Simplex method). The exact approaches for the LRP have been limited to small- and medium-sized instances with 20–50 customers[108]. In a large-scale problem size and also due to the complexity of LRP, the heuristic approach is proposed. The classification of solution methods in LRP according to Nagi and Salhi[76] is divided into three categories: iterative, clustering, and hierarchical-based algorithm. The improving solution with repeating the algorithm is called iterative. In the clustering algorithm the first step is to set the customers into clusters, assign the customers to the potential depots (or vehicle routes) and then follow this by solving the location and routing. The hierarchical set the algorithm into main algorithm that solving the location problem and the sub algorithm that the routing part[68]. Wu et al.[107] proposed the simulated annealing associated with the tabu list to avoid cycling for the multi-depot LRP with heterogeneous vehicle types with a limited number of vehicles and capacity on both routes and depots. Yu et al.[108] also proposed the simulated annealing heuristic. In the dissertation of Sajjadi[90] there are several literature reviews about the heuristic solution. One of them is from Nagy and Salhi[76] who presented a capacitated vehicle with a nested heuristic solution and distance limitation. They divided the problem into location as master problem and routing as the sub problem. The computational result suggested that their method had better results than the sequential algorithm. There are some criteria which needed to be considered for evaluation purposes in MDLRP according to Ball and Magazine in Srivastava[99]. These include:

- How close is the solution to being optimal?
- the computer running time and storage space for the heuristic;
- flexibility of the heuristics is an important consideration, since changes in the model required by different real-world problems should be easily handled;
- simplicity and analyzability of the heuristics.

The LRP has the complexity of the two sub problems of location and routing. In realistic problems the optimal solution procedures may not be possible, thus the heuristic procedure has been developed to solve this problem.

The sub problems of LAP are solved with the ADD and DROP heuristics. The following definition of ADD and DROP heuristics is according to Daskin[15] and Jacobsen[43] . The ADD procedure is a greedy algorithm. In each iteration a depot is greedily added to the solution until the algorithm is not able to find a depot where the largest saving can be obtained. “Greedily” means that each depot that is added to the solution reduces the cost as much as possible.

Table 5.2. Classification of LRP with regard to its solution method[52]

Solution Methodology		Methods and Algorithms
1	Exact Algorithm	Direct tree search/ Branch and bound Dynamic programming Integer programming Nonlinear programming
2	Heuristic	Nearest Neighbour Heuristic Savings / Insertion Improvement / exchange
3	Meta-Heuristics	Ant Algorithms Genetic Algorithms Simulated Annealing Tabu Search

The DROP procedure is also a greedy heuristic. In each iteration a depot is removed at the location where the largest saving is obtained until the algorithm can no longer find a depot whose removal will result in a decrease in the total cost. “Greedily” now means that each depot that is removed from the solution reduces the costs as much as possible. To describe the ADD and DROP procedure in the next section, the following additional notation will be used [106]:

I = the set of location

I_0 = subset of I that has been decided to close

I_1 = subset of I that has been decided to open

I_2 = subset of I that is yet undecided

5.2. The minimum cost method

The first step of the proposed ADD and DROP procedure requires the solution of the transportation model to solve the LAP. The transportation problem in this model was solved by the cost savings method. The transportation problem in general can be characterized by the following description[106]:

- A set of m supply points from which a good is shipped. Supply point i can supply at most q_i units;
- A set of demand points to which the good is shipped. Demand point j must receive at least wj units of the shipped good;
- Each unit produced at supply point i and shipped to demand point j incurs a variable cost of cij.

In the LAP the adopted following mathematical model from Jacobsen[43] was examined. The data for the LAP model are:

a_i : fixed cost associated with *i* th location

c_{ij} : cost of supplying one unit volume to the *j*th customer from *i*th location

w_j : demand from customer j

q_i : maximum output from location i

I : the set of locations

J : the set of customers

The decision variables are :

Z_i : indicates whether (z = 1) or not (z = 0) a facility is established at location i

x_{ij} : volume shipped from location I to customer j.

The objective is to minimize total location cost and transportation cost.

$$\min \sum_{i \in I} a_i z_i + \sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij} \qquad (5.1)$$

Subject to:

$$\sum_{i \in I} x_{ij} = w_j, \quad j \in J \qquad (5.2)$$

$$w_j z_i - x_{ij} \geq 0, \quad j \in J, i \in I \qquad (5.3)$$

$$q_i z_i - \sum_{i \in I} x_{ij} \geq 0, \quad i \in I \qquad (5.4)$$

$$z_i \in \{0,1\}, \quad i \in I \tag{5.5}$$

$$x_{ij} \geq 0, \quad j \in J, i \in I \tag{5.6}$$

Equation (5.1) shows that the objective function is to minimize the total location and transportation costs. Constraint (5.2) ensures the demand could be satisfied from all locations. Constraint (5.3) shows that only positive shipments are possible. Constraint (5.4) ensures that only positive outputs of locations are considered. Constraint (5.5) indicates whether the facility is established or not. Constraint (5.6) ensures only positive demand is possible.

The main characteristic that distinguished the minimum cost method from other solution methods such as the northwest corner method is the consideration of using up as much of the available supplies or requirements (the distribution costs) at as small a cost as possible to produce a lower total cost. The steps in the minimum cost method are described below[106]:

1. Find the variable which has the smallest distributed cost (call it x_{ij}).
2. Assign x_{ij} its largest possible value.
3. Cross out row *i* or column *j* whose availability or requirements are exhausted, and reduce the supply or demand of the non-crossed-out row or column by the value of x_{ij}.
4. Choose from the cells that do not lie in a crossed-out row or column the cell with the minimum distribution cost.
5. Repeat the procedure until there is only one cell that can be chosen. In this case, cross out both the cell's row and column.

Using this method the initial feasible solution in the LAP level is obtained: to get the assignment of the customers to depots that gives the minimum total cost.

5.3. ADD HEURISTIC PROCEDURES

The procedure of the ADD heuristic was developed initially by Kuehn and Hamburger[56] for the un-capacitated plant location model. In this thesis the adopted procedure from Jacobsen[106] is used. The ADD heuristic normally leads to bad solutions[20]. The ADD procedure usually starts with zero depots. It is difficult to choose which depot to open first and, in order to overcome this difficulty, a starting procedure from Domschke and Drexl[20] was used .

This procedure could also be mentioned as the initial solution, because in this starting procedure, the depots that should be open have already been found but are not yet optimal. The description of the starting procedure is as follows: the locations from the candidates' depot are added in order of decreasing values of the mathematical model below until the depots opened are able to serve the entire demand of all retailers[20].

$$\text{cost saving} = \frac{\sum_{j=1}^{n} b_j}{\sum_{j=1}^{n} c_{hj} b_j} a_h - f_h$$

The mathematical model above explains that locations *h* whose reciprocal of average transportation costs C_{hj} for serving all demand b_j from customers, multiplied by capacity of depot a_h and decreased by fixed cost of depot f_h, is least are selected. In other words, among locations with equal transportation and fixed costs the capacity is the deciding factor. Among locations with equal capacities and transportation costs the fixed costs are the deciding factor. Among locations with equal capacities and fixed costs the transportation costs are the deciding factor. After getting the depot (named by super source SS) in locations which are able to serve the entire demand, the procedure is continued with the the ADD heuristics from Jacobsen[43].

After the starting procedure for the ADD procedure was calculated the steps were continued for the ADD procedure where a facility is added at the location which obtains the largest saving as follows[43]:

1. Initially only the depot from the starting procedure was opened, which was mentioned as “super source (SS)”, and was symbolized by I_1.
2. For each depot (i) that belongs to the candidates’ depots (I_2) or $i \in I_2$ compute the saving cost (A_{i0}) with the formula below:

   $$A_{i0} = C^*(I_1, J) - C^*(I_1 \cup \{i_0\}, J) - a_{i0}$$

where A_{i0} : saving cost,

$C^*(I_1, J)$: the optimal objective of the transportation model with source set I_1.

3. Find the depot that has the largest saving depot *i* (i^* such that $A_{i^*} = \max_{i \in I2}\{Ai_0\}$).
4. If $A_{i^*} > 0$, i^* is transferred from I_2 to I_1 and another iteration is made. If $A_{i^*} \leq 0$, the elements of I_2 are transferred to I_0.
5. Computations are discontinued when the savings cost is less than zero, which means a solution is available.

The computation in step 1 is the saving cost by adding a facility at i_0 while all other locations in I_2 are considered unused. The computation of A_{i^*} in step 1 requires the solution of I_2 transportation models in each iteration.

5.4. DROP HEURISTIC PROCEDURES

The DROP procedure was first used by Feldman, Lehrer and Ray (Sridahran[98]) for un-capacitated plant location problems. This procedure dropped a depot in each iteration at the location where the largest saving is obtained. The steps are described below:

1. Start with all depots opened.
2. Initially, all locations contain a facility. That means I_2 is the set of all locations.
3. For each depot (i_0) in the candidates’ depots (I_2) or $i_0 \in I_2$ compute :

   $$A_{i0} = a_{i0} + C^*(I_2, J) - C^*(I_2 \cup \{i_0\}, J)$$

4. Find the depot that has the maximal saving cost

   (i^* such that $A_{i^*} = \max_{i \in I2}\{Ai_0\}$).

5. If $A_{i^*} > 0$, i^* is transferred from I_2 to I_0 and another iteration is made. If $A_{i^*} \leq 0$, the elements of I_2 are transferred to I_1.
6. Computations are discontinued as a solution is available.

The Ai_0 computed in step 1 is the saving gained by dropping a facility at i_0 while all other locations in I_2 are regarded as containing a facility. The computation of A_{i^*} in step 1 requires the solution of I_2 transportation models in each iteration. To solve the transportation model, the minimum cost methods were used.

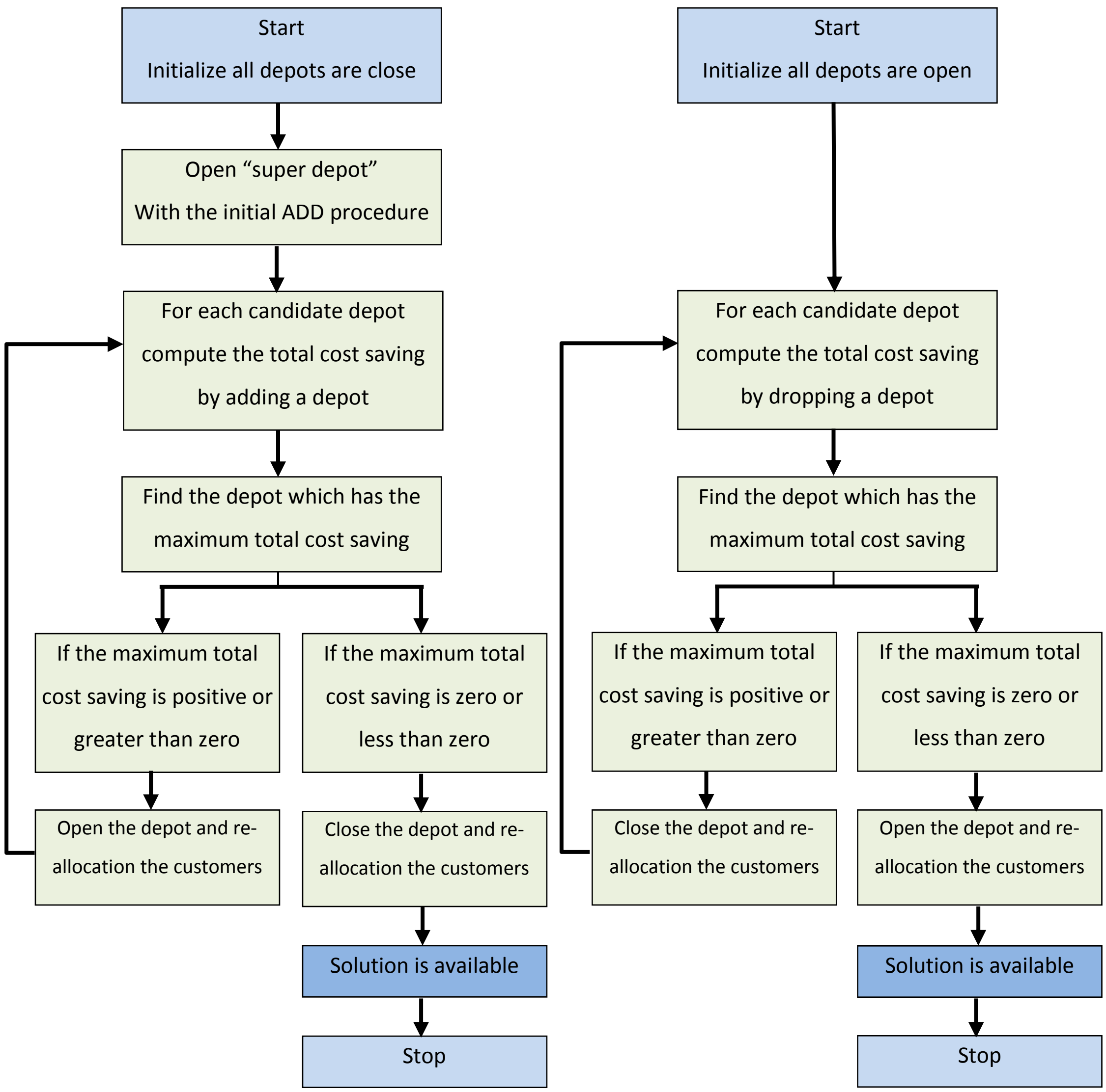


Figure 5.2. The Flowcharts for Add and DROP procedure (Inspired by Jacobsen[43])

5.5. Improvement in the routing level using the savings heuristic method

The savings heuristic was developed by Clark and Wright[11]. This procedure was designed to enable selection of an optimum or near-optimum route which a designed problem model of varying vehicle capacities with homogenous product. The objective is to allocate loads to vehicles in such a way that all products are assigned and the total distance of all routes covered is minimized. The distance savings is generated by merging two routes into a single route. The steps in the savings heuristic are described below:

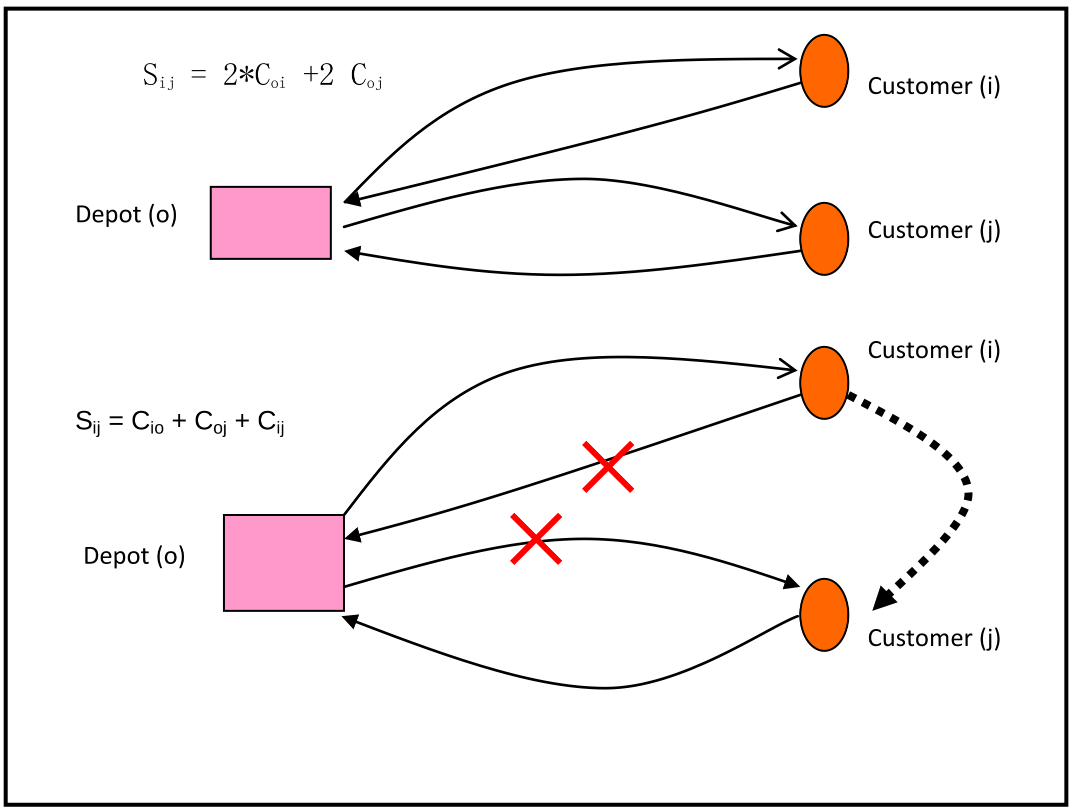


Figure 5.3. Step in savings method

<u>Step1. Savings Computation</u>

Compute the savings (S_{ij}) from every node of customer (i,j) that are connected to a depot (o) with the following equation:

$S_{ij} = C_{io} + C_{oj} + C_{ij}$

Create *n* vehicle routes (0,i,0) for *i = 1,….,n*. and then list the savings in a non-increasing manner.

<u>Step 2. Merge the routes</u>

Execute the following steps starting from the top of the saving listing, calculate a saving S_{ij}, and find out whether there are two routes that can feasibly be merged, starting with (*0,j*) and ending with (*i,0*). Combine these two routes by deleting (*0,j*) and (*i,0*) and introducing (*i,j*). In another explanation, there are two components of savings. The first is the distance route from customer i back to the depot adding the other one from the depot to the customer. The second part is the distance between these two customers. The first part can be saved and replaced the second part, which is the new connection between customers. In other words, the vehicle does not have to go back to the depot; instead it goes to the other customer and connects them. Consider the next route and reapply the same operations. Stop when no route merge is feasible. Figure (5.4) shows a snapshot of the results screen of the software developed.

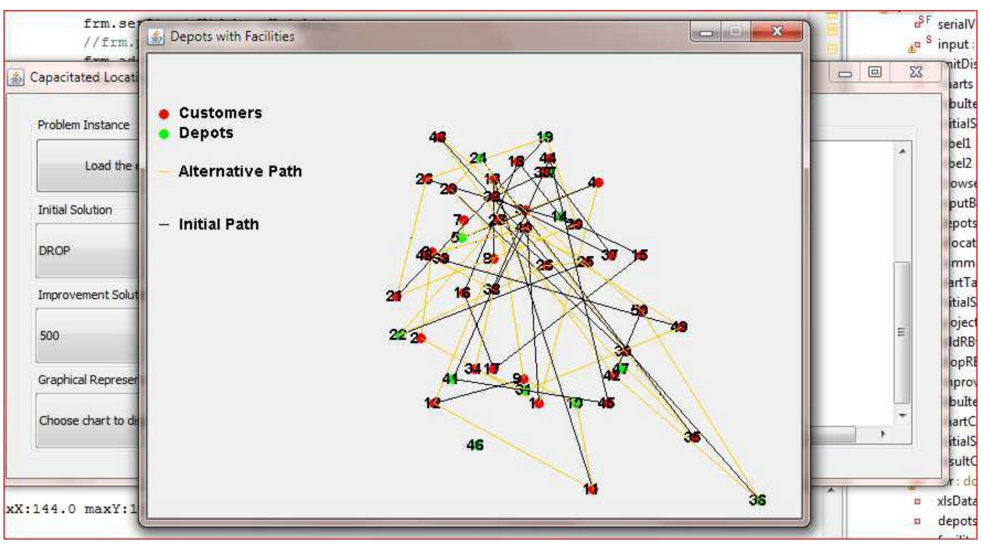


Figure (5.4) Snapshot of result screen of the developed software

6. Case study: Powder Detergent Industry

Detergent manufacturing consists of a broad range of processing and packing operations. The size and complexity of these operations varies from small plants, employing a few people, to those with several hundred workers. Production ranges from large-volume types to lower-volume specialties for less frequent cleaning needs. The different stages in the detergent supply chain is showed in figure (6.1).

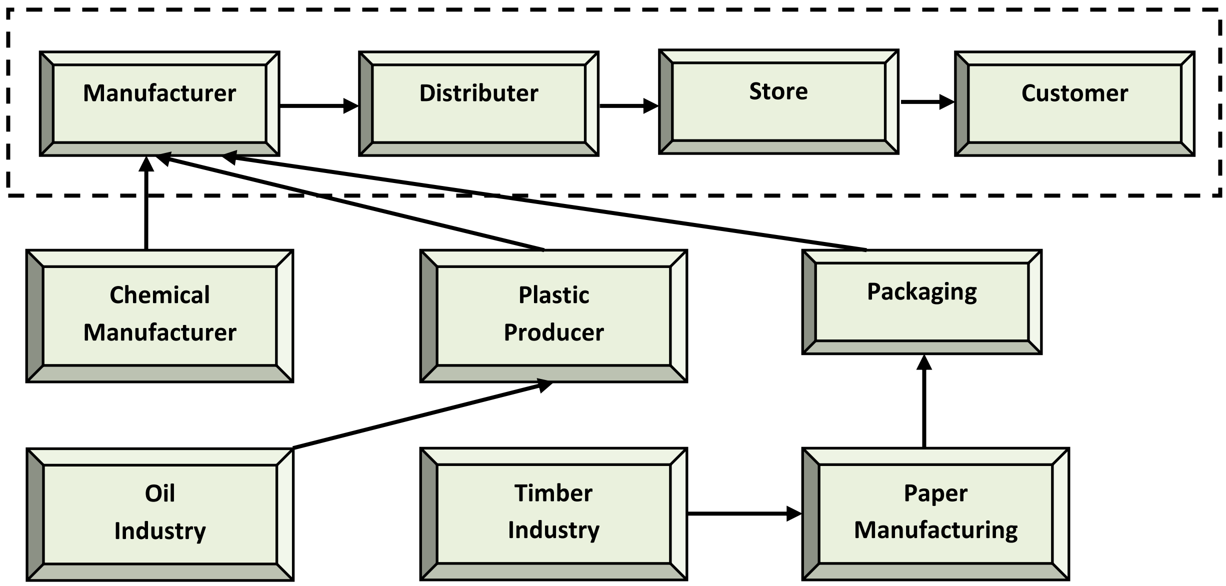


Fig. (6.1): The different stages in a detergent supply chain.

Published statistics on the market for laundry products are often unclear and contradictory. Based on publications on laundry product consumption, table 6.1 has been compiled, which presents the volumes of the main laundry products. For certain countries it has been necessary to extrapolate data based on information from countries with very similar cultural conditions, or from slightly older data. A consumption of approximately 25 million of the main laundry product has been estimated: 25% by the developed regions, and 75% by the less-developed regions.

Table 6.1 Laundry product consumption in 1994 and in 2010 [114]

			Consumption	
	GNP	Population	1994	2010
	(U.S.S/capita)	(millions)	(tons)	(tons)
World		5.605.7	25.318.110	30.907.400
Developed areas				
USA/Canada	22.839	289.9	2.174.250	2.503.500
Western Europe	20.103	382.9	3.063.440	3.117.840
Japan	28.220	125.0	875.000	912.800
Australia/New Zealand/Singapore	16.187	24.2	193.600	226.400
SUBTOTAL		822.0	6.306.290	6.750.540
PERCANTAGE OF TOTAL		14.7%	24.9%	21.9%
Less-developed areas				
Latin America	2.688	469.2	3.284.680	4.088.000
Eastern Europe	2.295	353.9	2.477.440	2.434.810
Western Asia/Middle East	1.983	415.1	2.075.500	3.190.500
Northern Africa	1.077	157.6	788.000	1.102.500
Sub-Saharan Africa	486	541.8	1.625.400	2.572.800
India and others	301	1.069.2	2.673.000	3.457.250
China and others	380	1.194.4	2.986.000	3.449.000
Northeast Asia	6.328	94.9	664.300	763.000
Southeast Asia	855	487.5	2.437.500	3.089.000
SUBTOTAL		4.783.7	19.011.820	24.146.860
PERCENTAGE OF TOTAL		85.3%	75.1%	78.1%

This case study is based on a plant which produces multiple products of different sizes. The production of sprayed detergent powder is obtained through three subsequent major steps:

- Preparation of a mixture of solid and liquid components, called slurry, forming a suspension with H2O content varying 30–40%.
- Drying of the slurry by means of high-pressure spraying in a vertical cylindrical tower, in contact with a stream of hot air.
- Performing of sprayed product and possible introduction of other additives, which, for different reasons, cannot be added during the slurry preparation.

The following are the main steps to produce these products.

6.1 Process description

Standard detergent powder manufacturing consists of slurry making, spray drying, after drying, and packing and antipollution units. These steps are briefly described as follows.

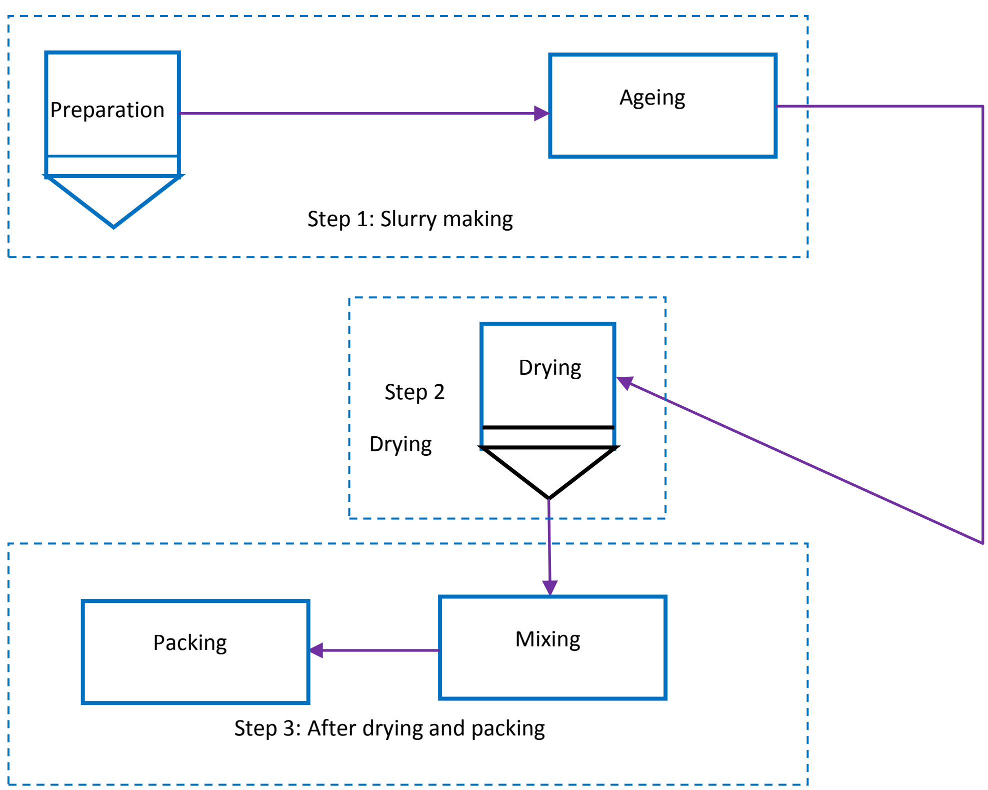


Fig. (6.2): Process flow chart

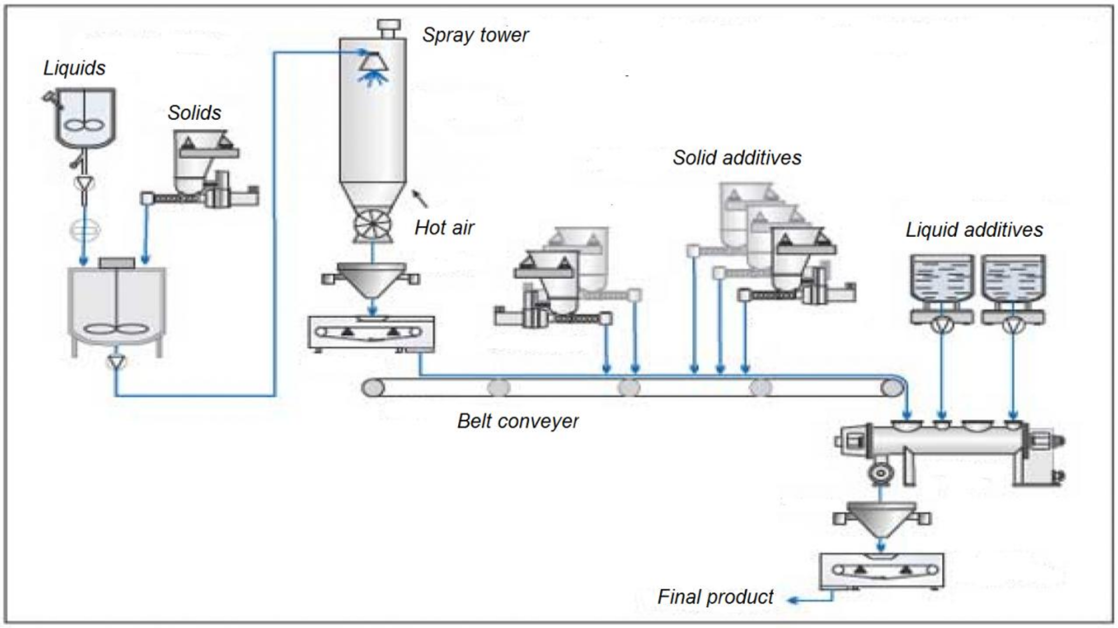


Figure (6.3) Main production processes[114]

The plant layout for detergent formulations consists of a feed-preparation section (automatic feeding, proportioning and mixing), feed pumping to the nozzle atomizer, dried-powder conveying and dosing, followed by thorough blending, screening and packaging.

6.1.1 Slurry making

In the slurry making process, dry and liquid ingredients are first combined into slurry, or thick suspension, in a tank called a crutcher. The slurry is heated and then pumped to the top of a tower where it is sprayed through nozzles under high pressure to produce small droplets. The droplets fall through a current of hot air forming hollow granules as they dry. The dried granules are collected from the bottom of the spray tower where they are screened to achieve a relatively uniform size.

In the detergent processing plant the detergent powder is normally produced in batches or continuously.

Linear alkyl benzene sulphonate paste is metered into a slurry preparation tank together with metered sodium silicate solution, solid phosphates, sulphates and additives. The slurry preparation tank acts as a coarse mixer: lumps are broken down and air pockets are eliminated. After blending, materials are conveyed to an ageing vessel.

Mixing is carefully controlled to prevent aeration of the slurry. Feed slurry passes through a coarse filter, a homogenizer and then a fine filter; deaeration of the product is carried out if necessary. The slurry, which is now of a consistent solidity and viscosity, is ready for spray drying. The handling of the product in the feed treatment section plays a large role in the quality of the dried product (e.g., granulation, degree of fines, etc.).

The solid and liquid raw ingredients are dropped into a large tank known as a slurry mixer. As the ingredients are added, the mixture heats up as a result of two exothermic reactions: the hydration of sodium tripolyphosphate and the reaction between caustic soda and linear alkylbenzene sulphonic acid. The mixture is then further heated to 85°C and stirred until it forms a homogeneous slurry.

6.1.2 Detergent Spray Drying

In the current high-tonnage productions of spray-dried detergents, continuous mixing of ingredients is used to form formulations that can be spray dried in drying towers with nozzle atomization. Many spray towers have the built-in flexibility of both co-current and countercurrent air flows in order to handle special formulations and achieve specific bulk density.

The plant layout for detergent formulations consists of a feed-preparation section (automatic feeding, proportioning and mixing) feed pumping to the nozzle atomizer, dried-powder conveying and dosing, followed by thorough blending, screening and packaging.

The slurry (50–80°C, 120–180°F) is fed to the spray dryer by a high-pressure pump. Countercurrent product airflows are mainly used. A countercurrent unit with multiple nozzles has been claimed to be of special merit, and countercurrent systems also give high-bulk densities of 0.3–0.4 g/cm3 and moisture content of 6–15%. Cocurrent systems give low-bulk densities of 0.1–0.3 g/cm3 with moisture content of 3–8%.

The vast majority of powder leaves the base of the chamber. The entrained fines fraction is recovered from the exhaust air in cyclones or bag filters, and these fines are reslurried.

The main product is conveyed by belt to an airlift. Any after-drying dosing is carried out on the belt: this can be organic foam boosters (lauryl alcohol), enzymes (proteolytic) and sodium perborate. The airlift then raises the powder to a storage hopper from where a gravity feed takes the product through screens and a perfuming chamber and on to the packing machines.

6.1.3 Pneumatic Conveying, Perfuming and Packing

The dried detergent powder is pneumatically conveyed from the spray dryer to the product silos, after sieving. Here filtered atmospheric air is used as the cooling and conveying media; dense phase conveying systems are normally preferred. The detergent product from the silo is then blended along with the perfume in a continuous mixer, after which it is packed.

6.2 Product characteristics

The detergent powder coming from the spray-drying tower will be white without coloured spots, in the form of beads with dimensions 0.2–2.5 mm. The density of the product (250–400 g/l) and the moisture content (13–19%) depends on the slurry composition and the drying conditions, and can be adjusted, within a certain range, by acting on the process parameters; i.e., slurry ageing time and temperature, spray-drying pressure, hot air temperature, exhaust air temperature, etc. There is a wide range of formulations for hand-washing and machine-washing detergent powder.

There are three main dimensions for the products. Table 6.2 shows these dimensions.

Table 6.2: Products dimensions

No.	Code	Denomination	Dimensions (mm)		
			H	W	TH
1	RB 11	E1	117	42.5	155
2	RB 12	E2	143.5	53.5	200
3	RB 13	E10	251.5	103.5	333

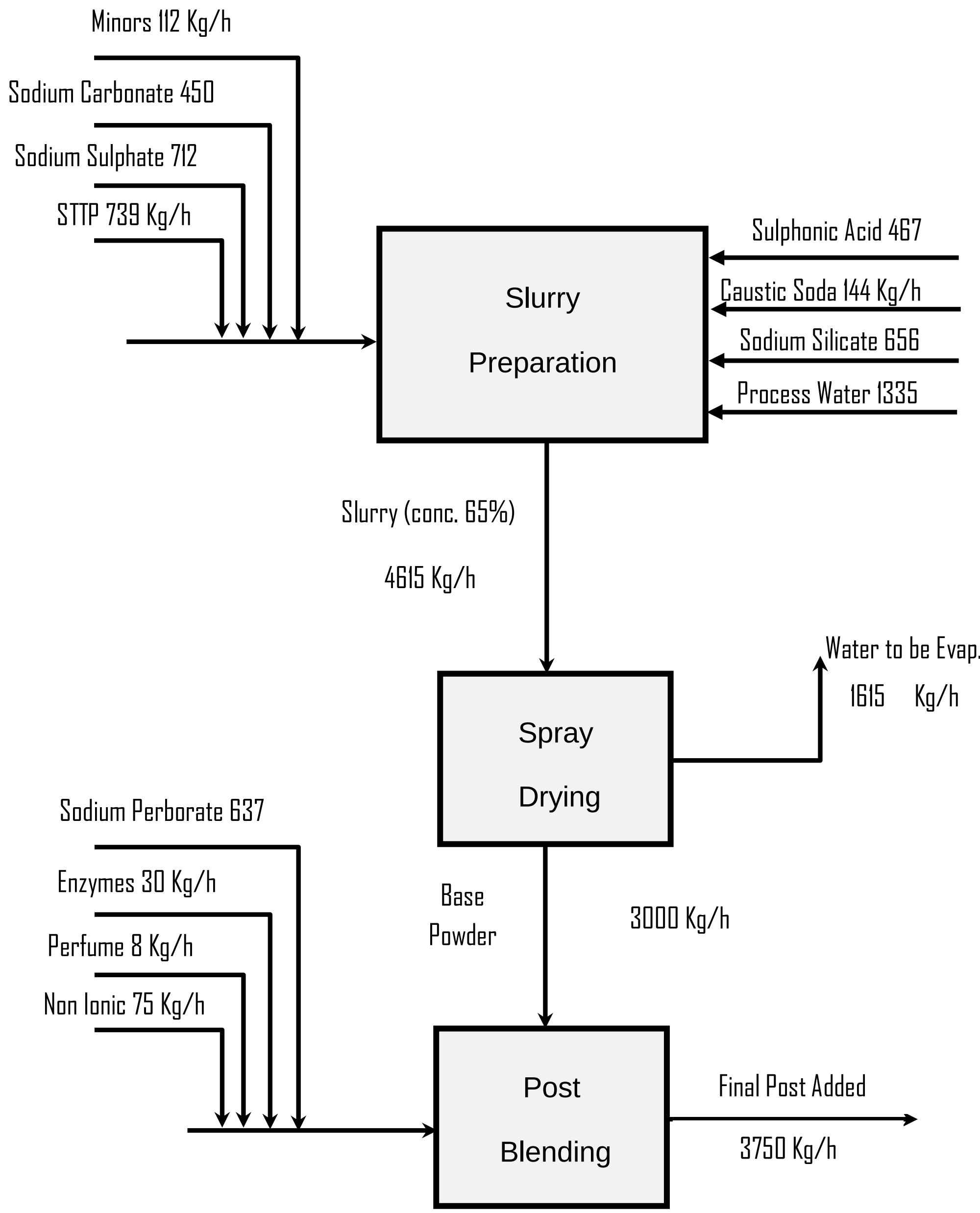


Fig. 6.4: Main stages and raw material

When the characteristics of the package change (carton dimensions, filling volume) the following amendments are necessary (at the packing machine):

- Replacement of size parts.
- Adjustment as necessary.
- Timing reset of the machine according to the new configuration caused by the replacements and adjustments that were executed.

Because of these adjustments, there are setup times between different products. Table 6.3 shows the setup time in general (in minutes) at the packing machine.

Table 6.3 setup time matrix (in minutes) at packing machine.

Domination	**E1**	**E2**	**E3**
E1	10	30	90
E2	30	10	90
E3	90	90	0

Appendix I, II shows the setup time matrix at packing and drying machines in details.

Also, there is a setup time at the preparation stage between the product P_3 and the other products.

Table 6.4 shows the production rate and carton sizes for every type of product.

Table 6.4: production rate (in tons)

Nom.	E_1	E_2	E_3
Weight	140 g	200 g	3 kg
Production rate (ton)	3	3	3
No. of units per carton	48	24	4

The setup cost consists of manpower cost and depreciation cost of the tools used. The main cost factor is the sales losses. The plant capacity is 3 tons/hour. That means that for every idle hour the plant will lose sales equal to the estimated income of this production.

7. Calculations and Analysis

In this chapter the results and analysis of the case study are presented. In these calculations and analysis two scenarios are presented: the first scenario where the manufacturer is dominant, and the second scenario where the production, inventory and routing is synchronized. The calculations will be as the following:

- Solving the job scheduling problem to find the optimum schedule for the plant. This solution has been found using the NEH algorithm with setup time. Using this solution, the transporter delivers the quantity according to the VMI model. The calculations for the VMI model consider two scenarios. The first one is the 'one truck one product' model, and the second is 'one truck multi products'. Also the results of the inserting impeding products and customers' concepts have been showed.
- The synchronizing production, inventory and distribution routing is considered later. In this model the software SimAL has been used to find the optimum job schedule.
- The last part of the calculations shows the effect of transportation cost on the suggested model.

7.1 Manufacturer dominates model

The objective of the manufacturer is to minimize the total setup time (setup cost), and any schedule that minimizes this time is optimum; using the NEHT algorithm provides the optimum schedule.

The total setup time, according to this sequence, is five hours.

The setup costs consist of many elements; for example, labour, materials, tools, and quantity losses costs. The last cost is the major cost. The production quantity per hour is three tons, which means the plant loses three tons of sales every hour.

The average setup cost = total setup time (hrs) * 3 tons/ hr* average price.

The minimum (optimum) setup cost for the plant is 48,750.

According to this plan, the distributor will deliver the required quantity to the customers. There are two scenarios: the first scenario uses the VMI model, and the second scenario uses the VRP model.

7.2 Using the VMI model

7.2.1 Assigning retailers to depots

After making a selection of seed retailers, start from any one retailer and begin to form the cluster. Calculate the distance from this retailer to all other retailers using the formula $d_{ra,rb}=\sqrt{(X_{ra}-X_{rb})^2+(Y_{ra}-Y_{rb})^2}$.

Subsequently, take the next retailer and apply the same approach to find out the nearest retailer. Repeat this algorithm until reaching the capacity limit of one depot. A review of table 7.1 suggests that R90 is the last point of cluster one.

Table 7.1: Cluster 1

Cluster1	R246	R245	……	R91	R90
Cumulative Weight	0.12	0.23	……	7.96	8.09

Through the calculations presented above, so far we have routed 80 retailers in cluster one. The other two clusters will be generated based on the remaining 166 retailers. As the routing algorithm is the same, we will omit the calculation process for cluster two and cluster three.

As illustrated in table 7.2, R246 and R90 represent the starting point and end point of cluster one, respectively; cluster two starts from R20 and ends with R168; R233 represents the starting point and the last point is represented by R89 in cluster three.

Table 7.2: Three Clusters and Stem Distance

Cluster	Starting point	Ending point	Total distance	Total demand in ton	Total demand in carton	Stem distance DC1	DC2	DC3
1	246	90	151.66	8.09	1,125	48.3	56.1	46.5
2	20	168	197.99	8.08	1,133	84.8	38.5	71.8
3	233	89	221.72	7.82	1,078	51.0	52.5	44.9

By applying step five with formula $\min(d_{stem})=\min((d_{DC1,r0}+ d_{DC1,rn}),\ldots\ldots(d_{DCn,r0}+ d_{DCn,rn})$ in phase one, solutions have been obtained as shown in table 7.2. It can be noted that DC1 is the closest depot to cluster one with a geographic distance of 48.3 km, DC2 has the smallest distance of 38.5 km to cluster two, and obviously DC3 is required to supply cluster three as it is located closer to this cluster than the other two depots.

7.2.2 Retailer Service Sequence List

According to available data, including initial inventory level I_r, customer consumption rate u_r by U_r/daily work hour (10 hours) with formula $T_{r,stoc}=I_r/u_r$, we can calculate the shortage time of each retailer. Unlike in previous studies where only one item forms the research objective, in our study, there are three products that require delivery from suppliers to customers. Thus, when we calculate the stock-out time for each retailer, the three products should be considered simultaneously.

Let us take R245 in cluster 1, for example. As shown in table 7.3, the initial inventory levels of product one is seven cartons; the consumption rate is two cartons per day; we can work out the stock-out time with the given data. If we assume our simulation horizon does not exceed ten hours, then 35 hours means R245 will not be supplied with product one in the current period. However, these figures are only concerned with one product; therefore it is necessary to calculate the inventory levels of the other products. Obviously there also needs to be a sufficient amount of product two to ensure that R245 will not run out of product in 11.7 hours, but the situation varies for product three, with a shortage time of 6.7 hours, which is included in our consideration.

Table 7.3: Stock-out Time List

	Day 1								
	p1			p2			p3		
Retailer	Inventory Level	Consumption Rate	stockout time	Inventory Level	Consumption Rate	stockout time	Inventory Level	Consumption Rate	stockout time
84	6	5	12.0	5	1	50.0	3	1	30.0
85	3	3	10.0	5	2	25.0	1	1	10.0
90	5	1	50.0	8	7	11.4	1	4	2.5
⋮									
245	7	2	35.0	7	6	11.7	2	3	6.7
246	2	3	6.7	3	7	4.3	2	2	10.0

Not only do we need to calculate the stock-out time as the basis of vehicle assignment, but also, it is more important to order retailers according to the sequence of stock-out time, from small to large. Some retailers require a delivery of product one in the next hour, but other retailers may also require other products at the same time. That makes the delivery schedule especially difficult. How to decide the service sequence is basically determined by the urgency of the customers. One retailer with either one or more products being deficient would be placed at the top of the service sequence list.

7.2.3 Vehicle Assignment

The objective of this section is to partition retailer service sequence lists by looking at their demands and the summation of demands in accordance with vehicle capacity, to find out the most optimal solution that can minimize the total distribution cost.

7.2.3.1 Model 1: One truck – One product

In this model, one vehicle is responsible for delivering only a single product. Based on this premise, it is relatively easy to decide how much product to transport and which route to travel. Firstly, the total retailer service sequence list must be split into three separate lists with each one representing the stock-out time for one product.

As shown in table 7.4, this is part of the service sequence list for product one. According to the algorithm stated previously, R234 with the smallest stock-out time of 1.4 hours is defined as the most urgent retailer and will be served first. Starting from the initial time of zero, a truck leaves the depot and travels to R234 and arrives after 0.2 hours, represented by arrival time in the yellow area. During this time, from the depot to R234, the truck has travelled a distance of 15.6 km. Using the formula $t_{int}=d_{x,y}/v$, assuming a vehicle speed of 70 km/h, we can calculate the arrival time at the first retailer. Based on the available data, it usually takes quarter of an hour to unload at each retailer, which has to be taken into consideration when calculating the departure time from each retailer. This is the reason why the departure of the vehicle takes place 0.25 hours after arrival.

Table 7.4: Service Sequence List of product one

Retailer	Ordered Quantity	stockout time	serve sequence	ac.OQ	Distance	adjusted order	inter distance	inter arrival time(hour)	arrival time	leaving time
234	7	1.4	1	7	15.6	234	15.6	0.2	0.2	0.47
115	5	2.5	2	12	35.8	180	19.7	0.3	0.8	1.00
180	5	2.5	2	17	19.7	115	16.1	0.2	1.2	1.49

During the research, we encountered a problem where more than one retailer required a delivery at the same time, as demonstrated in table 7.4. Both R115 and R180 were due to run out of product after 2.5 hours. What must be made clear is that the urgency of the retailers in our study is defined as the most essential criterion in vehicle assignment. Only when this condition is satisfied would we consider applying another criterion such as distance, widely used in TSP, to solve the problem as the case shown in table 7.4 illustrates. However, in this example there is a distance of 35.8 km from R234 to R115, while from R234 to R180 the distance is only 19.7 km. Obviously R180 is the better solution when determining the next retailer in the sequence after R234. Thus, the service sequence has been adjusted from R234 to R180 and then from R180 to R115. With this adjustment, a distance of 16.1 km (35.8 - 19.7 = 16.1) has been minimized with a decrease in travel time of 0.23 hours (16.1/70 = 0.23).

7.2.3.2 Model 2: One truck – Multiple products

This model aims to control the number of truckloads not exceeding one. This means a retailer is visited only once a day by a truck, with three products being replenished in the same delivery.

In this model, an amount of three different products loaded in one truck is to be delivered to retailers in a trip. Each retailer has its own inventory capacity, average demand for each product and different requirements for the delivery period, which dramatically impacts on the complexity of creating efficient delivery routes; therefore, it is much more difficult to decide how much to transport and which route to travel than in model one.

As shown in table 7.5, this is a service sequence list associated with three products being delivered to nine retailers by one truck. According to the algorithm stated previously, R234 is the first customer to be visited. As every retailer is to be supplied only once a day, all the demands for products one, two and three must be satisfied in this truckload. We have assumed that the delivery quantity of each product is predetermined in both models; we don't need to consider the current demand of customers based on the arrival time at the customer to calculate the accumulative volume in the vehicle. Thereby, the delivery quantity to R234 is calculated by the sum of individual needs, which is 18 (7 plus 8 plus 3).

Table 7.5: Service Sequence List for Products 1, 2 and 3

Retailer	Ordered Quantity	P1 stockout time	Ordered Quantity	P2 stockout time	Ordered Quantity	P3 stockout time	ac. OQ	compared distance	adjusted order	inter distance	inter arrival time (hour)	arrival time	leaving time
234	7	1.4	8	20.0	3	5.0	18		234	15.6	0.2	0.2	0.47
183	7	6.0	8	5.0	5	2.0	38		222	14.1	0.2	0.7	0.92
222	7	7.1	8	2.0	3	30.0	56		194	15.8	0.2	1.1	1.40
99	7	7.5	6	2.0	5	15.0	74		183	2.2	0.0	1.4	1.68
194	7	15.0	6	60.0	5	2.0	92		99	19.1	0.3	2.0	2.20
90	0	50.0	8	11.4	5	2.5	105		90	3.0	0.0	2.2	2.49
201	7	2.9	0	20.0	5	50.0	117		201	23.5	0.3	2.8	3.08
181	7	3.3	8	3.3	3	5.0	135		181	4.0	0.1	3.1	3.39
113	5	10.0	5	3.3	2	20.0	147		113	17.2	0.2	3.6	3.88

where ac.OQ is the accumulative ordered quantity.

As the restriction of ten hours' working time has not been reached and there are no efficient items to serve another customer after R113 (see table 7.4), the truck has to return to the depot to reload for the next trip.

Other trucks at the depot are also assigned trips in this way until all the retailers are served by any one of them.

7.2.4 The analysis of model 1 and model 2

According to the raw data for cluster one and the different algorithms used in the two models above, the total system costs by applying model one and model two are obviously different. As both models are subject to the constraint that the delivery quantities must be constant, there is no difference in the inventory cost between the two models based on the same initial inventory level and consumption rate. Therefore we only need to compare the total travel distance resulting from each model.

From table 7.6, we can see the following:

(1) In model one, eight trucks are needed when the same number of retailers are served. Each truck travels once a day with a total travel distance of 1796 km.
(2) In model two, although only half of the number of vehicles in model one are put into use, each truck delivers twice a day, on average, with a total travel distance of 1003 km.

Table 7.6: Comparison of model 1 and model 2.

	concept	No. of Trucks	total travel distance
Model 1	One truck is mainly in charge of one product Each truck delivers once a day	8	1796
Model 2	One truck delivers three product at once Each truck can have multi-tour for a day	4	1003

However, this situation could be complicated in reality, as retailers located widely require deliveries at different times and with specific demands. The most essential point in solving this issue is being able to control the time when the truck arrives at the retailer. According to the actual arrival time, we can calculate the specific demands of retailers, which therefore influence not only how the routes are chosen, but also a calculation of the inventory costs of retailers and depots. In other words, the more accurately the model reflects the real situation, the more complex the problem becomes, and also the more feasible it is for future research. Thus, it cannot be denied that model two provides us with a reasonable direction for improvements on the algorithm.

7.2.5 The Initial Optimization

In this section we look at how we can improve the feasibility of our basic model based on model two, discussed previously. As stated, the most important improvement is that a variable, representing the actual volume of retailers consumed before the truck reaches, will be introduced into the calculation of the actual demand quantity.

7.2.6 The Further Improvement

Based on the previous assumption, the situation may arise where a customer is supplied with one or two products on one day and then replenished with another product the following day, due to the demands of their various initial inventory and consumption rates. For example, if a retailer is due to run out of a product in fifteen hours, then it will be supplied with this product the following day instead of being replenished at the same time as other ordered products that have a stock-out time of less than ten hours.

Furthermore, it is possible that some retailers who are geographically close (and thus can be served on a single trip) will never be routed together because of their diverse stock-out times (optimal replenishment days differ). If they can be routed together under certain conditions, it would be a great change from how the VMI has been solved previously.

In our initial solution, the retailer service sequence list is always created before assigning routes, which is a concern for all urgent retailers who will run out of product in ten hours. Firstly, it may be that some urgent retailers have one product that has an urgent inventory level, while also stocking other kinds of products that have a safe inventory level; this can be classified into two sets: impending products and non-impending products. Impending products are those that will be consumed within between ten and twenty hours, while non-impending products, that have a safe inventory, can meet a two-day long demand at least. Secondly, the remaining retailers also can be classified into two sets: impending retailers and non-impending retailers. Impending retailers are those that require a delivery on the second day, while non-impending retailers will not need a delivery in two days (Figure 7.1).

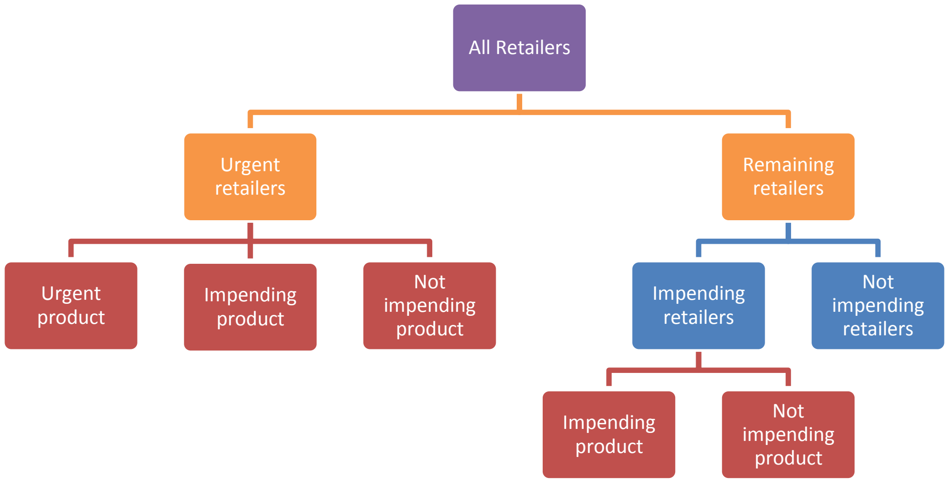


Fig. (7.1): Definition of retailers

7.2.7 Applying Insertion Heuristic

Once a set of delivery routes has been selected, some flexibility may exist in the individual routes in terms of constraints put on the available delivery time and quantity. Therefore, an insertion heuristic has been applied to improve vehicle utilization on this basis without causing stocking out.

Method 1: Insert impending products for urgent retailers.

Normally a retailer is served with product that will be consumed under an upper bound of ten hours; this can be defined as urgent product. The initial idea was to find geographically close retailers with impending products to include on one route. It would be a better choice to start with the urgent retailers with impending product. Thus, the first step is to check whether the first retailer on the first route has impending product or not. If yes, add the quantity, calculated through the formula, to the volume on the truck without exceeding the vehicle capacity. If no, go to the next retailer and repeat the step above.

According to table 7.7 and table 7.8, it can be noted that the latter one indicates a better solution. In table 7.7 there are three products with a total amount of 138 units on the truck. Compared with table 7.7, table 7.8 illustrates that 149 units of products are delivered to the same retailers on the route with eleven units more than the initial solution. The reason for this great difference lies in withholding product for R241 and R235, which are 4 and 7 respectively, presented by the colour yellow. Basically, this truck has been fully utilized through this approach.

Table 7.7: Route without Insertion

T1-1				
Retailer	P1 supplied Qty	P2 supplied Qty	P3 supplied Qty	ac.OQ
185	7	8	5	20
85	21	0	9	50
240	12	0		62
241		8	4	74
235		13		87
155		0	6	93
181	9	10	3	115
194	9	8	6	138

Table 7.8: Route with Insertion

T1-1				
Retailer	P1 supplied Qty	P2 supplied Qty	P3 supplied Qty	ac.OQ
185	7	8	5	20
85	21	0	9	50
240	12	0		62
241	4	8	4	78
235	7	13		98
155		0	6	104
181	9	10	3	126
194	9	8	6	149

Method 2: Insert impending retailers.

As mentioned earlier, impending retailers are those that require a delivery on the second day. If we only consider urgent retailers, according to the initial service sequence list, it is much easier to solve the problem. However, in the consideration of vehicle utilization, the solutions are not always quite what we want.

For example, consider the situation such as the one described previously, where there is a retailer A, included in the route, who is critical. The only retailers near A are B and C. If B is nearer to A than C, but is not urgent and C is urgent, then C should be served after A. However, if B is an impending retailer, then an opportunity exists for balancing the truckload by taking advantage of adjusting the route sequence. The basic idea is that we repeatedly add retailers to the model classified as urgent and impending retailers (Figure 7.2). All retailers that are currently considered in the model have an opportunity to be balanced if they require an impending delivery and are close to the route. Including these retailers with these attributes improves the chance of increasing truck efficiency. We do not consider non-critical and non-impending retailers without delivery require in the scheduled time in this phase in order to avoid causing large costs in terms of computation time.

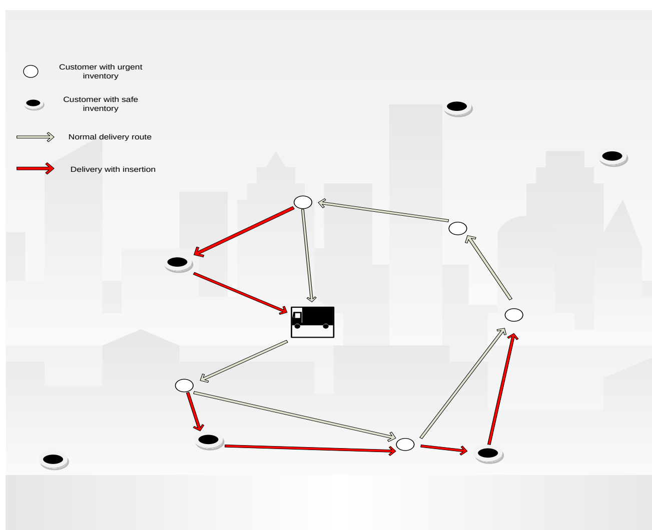


Fig. (7.2): Insertion of impending retailers

Method 3: Swap retailers between routes

All methods discussed earlier are based on a separate cluster. In our case all retailers and depots have been grouped into three clusters. This means a truck can only serve a retailer from the predetermined depot, which is in charge of all deliveries within this cluster. When we discuss transport costs and inventory costs, they will only be considered either within cluster one, cluster two or cluster three; there is no opportunity to create routes across the clusters. Eventually, the total costs generated in the whole distribution system will be calculated by the summation of individual costs brought together from each cluster.

However, the initial algorithm may not be the optimal solution for maximizing utilization and minimizing total operation costs. It may happen that two retailers are geographically close to each other, but are included in their respective routes, which belong to different clusters. If they were assigned to the same route, transport costs could be minimized due to a smaller travel distance in total. In figure 7.3, the retailer represented in yellow round could be switched to the right route, which could result in a greater minimization of the total travel distance for the whole distribution system.

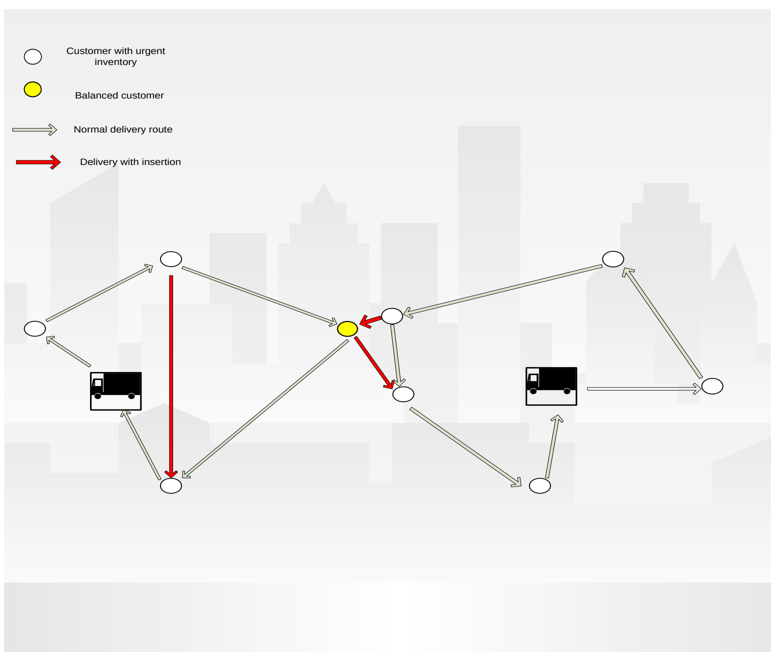


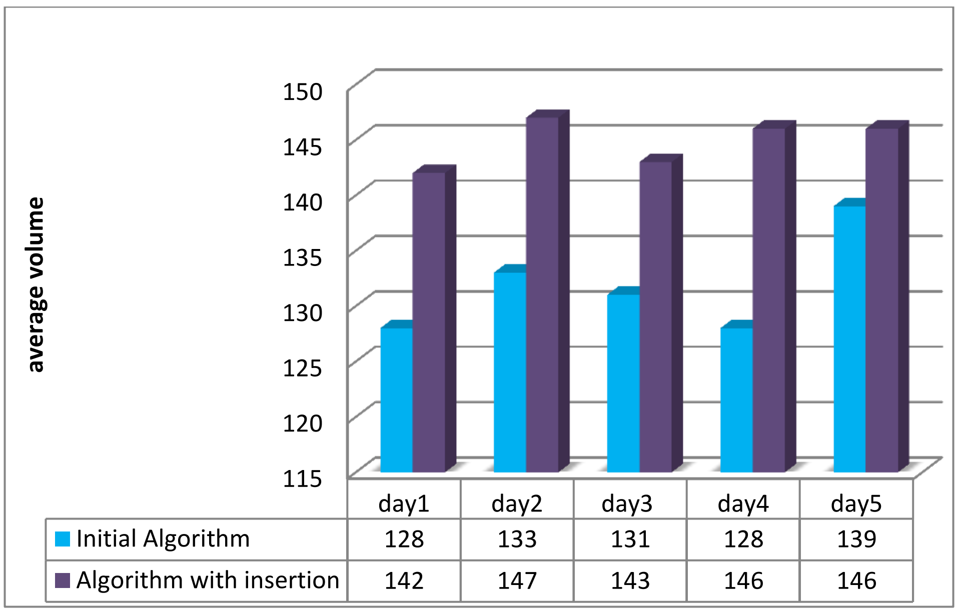
Fig. (7.3): Swap retailers between routes

7.2.7 Comparison and Analysis of Different Algorithms

In the previous section we have discussed several efforts to utilize vehicle capacity and reduce operational costs. To demonstrate the effectiveness of these efforts and the impact they have on our results, we applied the first two of all the methods in our experiment. We then compared the results obtained from the new approach with the initial algorithm without insertion.

For the comparison of simulation results, the following information will be taken into consideration:

(1) Vehicle utilization



	day1	day2	day3	day4	day5
Initial Algorithm	128	133	131	128	139
Algorithm with insertion	142	147	143	146	146

Figure (7.4): Comparison of vehicle utilization

Compared with the initial algorithm, the algorithm with insertion has a substantially higher vehicle utilization with approximate 145 units on average, thirteen units more than the 132 of the initial algorithm.

(2) Number of trips

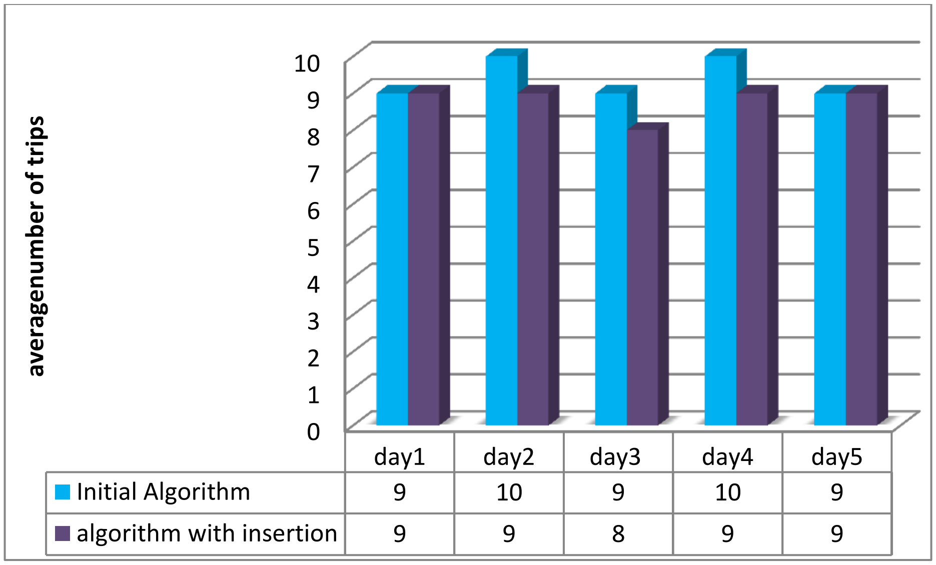


Figure (7.5): Comparison of number of trips

From figure 7.5, it can be seen that the algorithm with insertion provides a slight minimization in the number of trips when compared with the initial algorithm. Because the purpose of optimization is to utilize vehicle capacity to reduce the number of trips, as anticipated, it should usually be less than or equal to the solution from the initial algorithm.

(3) Cumulative delivered quantity

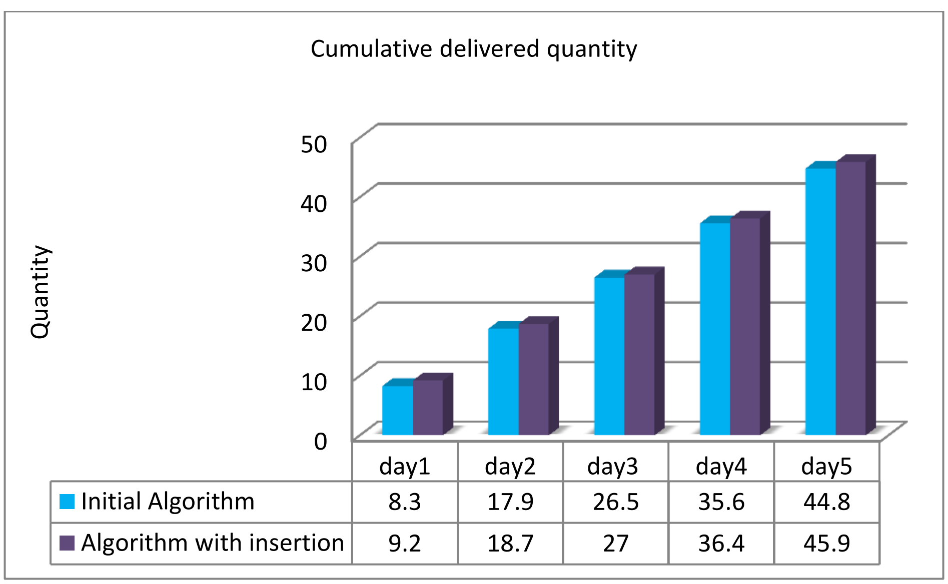


Figure (7.6): Comparison of cumulative delivered quantity

As shown in figure 7.6, a larger total delivered volume has been obtained from the new approach than that of the initial algorithm, this being 45.9 and 44.8 units, respectively, over a five-day period.

(4) Depot inventory level

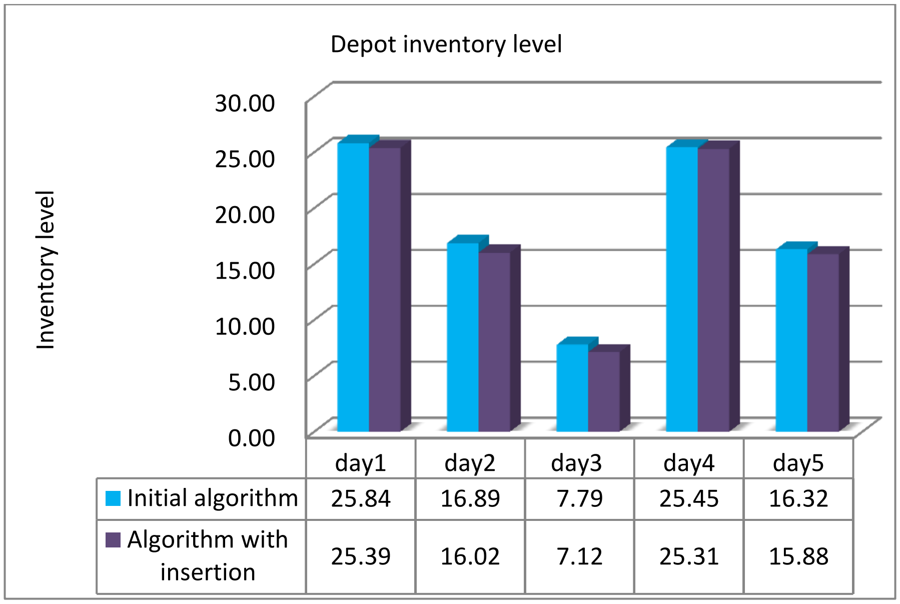
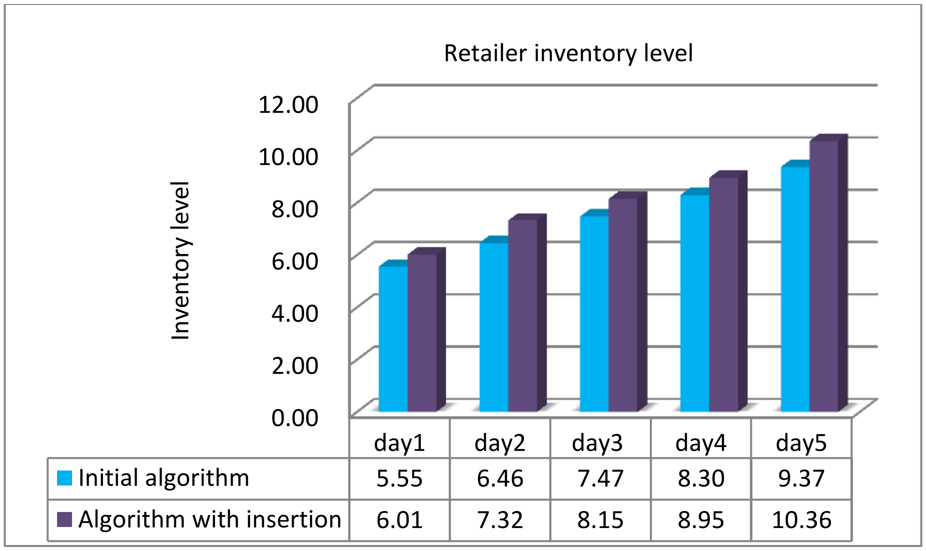


Figure (7.7): Comparison of depot inventory levels

According to the results indicated in figure 7.7, when more quantities are delivered from the depot to retailers, as shown in figure 7.6, it is logical that the algorithm with insertion results in a decrease of depot inventory level when compared with the initial algorithm.

(5) Retailer inventory level

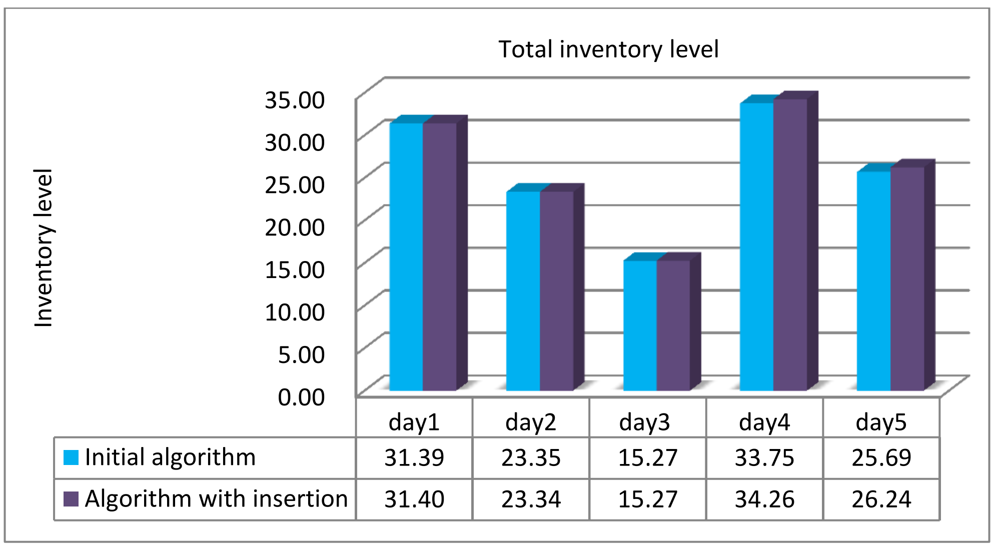
In contrast with figure 7.7, the algorithm with insertion results in an increase of retailer inventory levels when compared with the initial algorithm because more quantities have been delivered from the depot to the retailers.



	day1	day2	day3	day4	day5
Initial algorithm	5.55	6.46	7.47	8.30	9.37
Algorithm with insertion	6.01	7.32	8.15	8.95	10.36

Figure (7.8): Comparison of retailer inventory levels

(6) Total inventory level



	day1	day2	day3	day4	day5
Initial algorithm	31.39	23.35	15.27	33.75	25.69
Algorithm with insertion	31.40	23.34	15.27	34.26	26.24

Figure (7.9): Comparison of total inventory levels

Considering the total inventory levels of the depot and the retailers, as anticipated, the algorithm with insertion brings in a little higher storage level in comparison with the initial algorithm as the vehicle capacity is utilized and the delivery amount that we allow to be delivered is increased.

(7) Total travelled distance

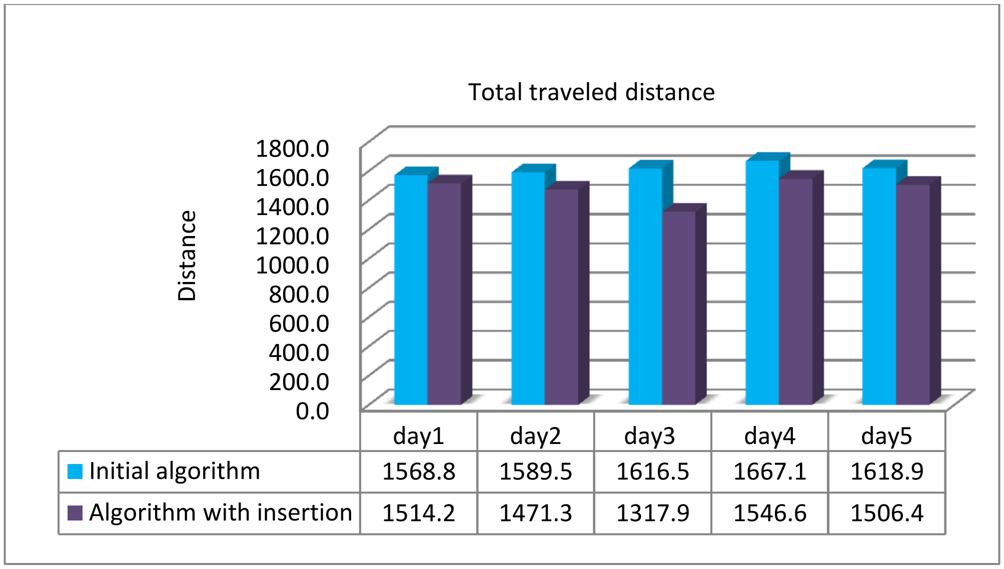


Figure (7.10): Comparison of total travelled distance

From the chart above, it is obvious that for the algorithm with insertion the total travelled distance is lower than that of the initial algorithm. With the same unit transport costs, clearly the delivery costs of the algorithm with insertion will be lower than the initial algorithm.

(8) Total costs

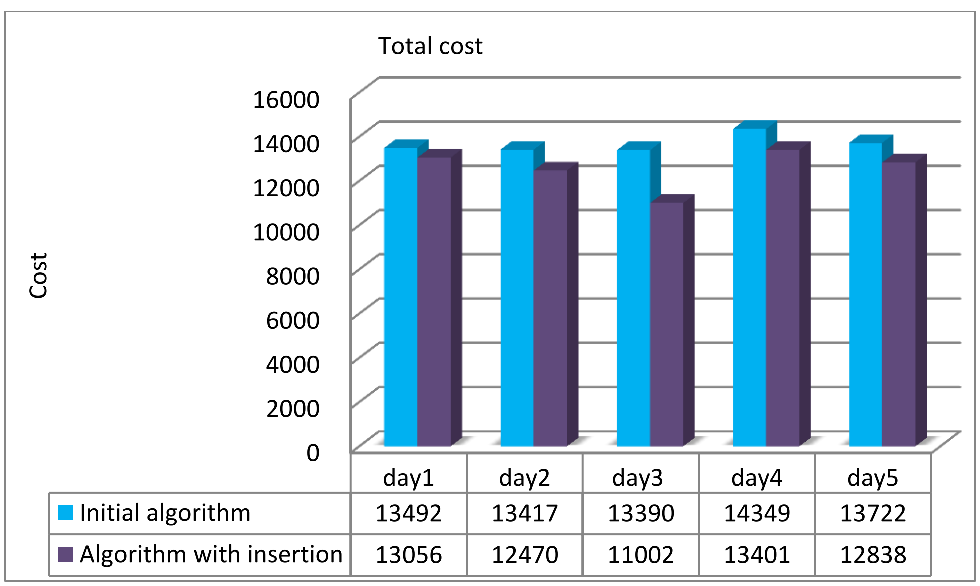


Figure (7.11): Comparison of total costs

From figure 7.11, it can be noted that the algorithm with insertion gives a substantially lower total cost for inventory and distribution when compared with the initial algorithm, which is just what we want from the further improvement.

In conclusion, we see that for our objective cluster, even with a larger total volume delivered, the algorithm with insertion has a substantially lower travel distance, higher volume per mile, higher average utilization, and lower total cost when compared to the initial algorithm.

This insertion approach tries to utilize vehicle capacity by including deliveries to retailers near the imminent retailers, which consume the remaining truck capacity in order to reduce transportation costs, especially fixed transportation costs. In the cases where the fixed transportation costs are very high, this approach will reduce the number of trips and distance that a vehicle must travel; therefore, the transportation costs will be remarkably reduced. Moreover, as the impending retailers are permitted to be replenished with a number of quantities based on the volume remaining on the truck, the total system inventory costs will be increased. However, the decreased transportation costs can compensate for the increased inventory costs; therefore, the total system costs will be minimized.

7.2.8 Inventory level of three depots

According to tables 7.9, 7.10 and 7.11, the inventory levels at each depot differ every day. Assuming that the depot inventory levels reach the upper bound of 30 tons on the first day, with daily deliveries to retailers, there will be no efficient products left in the warehouse at each depot for the next day´s supply at the end of day three. Based on the principle of not causing stock-out, replenishment for the three depots will be placed together earlier on the day four before the trucks at the depots transport products to the retailers. Delivery quantity to each depot can be obtained by subtracting from 30 the last inventory levels at the depot, which are 27, 27.3 and 25.3 respectively. This means that on day four there are, in total, 79.6 tons of items delivered from the plant to the depots.

Table 7.9: Inventory level of depot one

	Inventory Level of Depot(ton)				
DC1	Day1	Day2	Day3	Day4	Day5
I_i	30.0	20.8	11.3	30.0	20.6
I_{i+1}	20.8	11.3	3.0	20.6	11.1
average inventory	25.4	16.0	7.1	25.3	15.9

Table 7.10: Inventory level of depot two

	Inventory Level of Depot(ton)				
DC6	Day1	Day2	Day3	Day4	Day5
I_i	30.0	23.7	12.0	30.0	20.7
I_{i+1}	23.7	12.0	2.7	20.7	10.9
average inventory	26.8	17.9	7.3	25.3	15.8

Table 7.11: Inventory level of depot three

	Inventory Level of Depot(ton)				
DC7	Day1	Day2	Day3	Day4	Day5
I_i	30.0	24.9	12.1	30.0	20.6
I_{i+1}	24.9	12.1	4.7	20.6	12.1
average inventory	27.5	18.5	8.4	25.3	16.3

As illustrated in table 7.1, it takes 0.35 hours (at the most) to travel from the plant to the depot. As there are only three depots to be serviced, a direct delivery can be first scheduled from the plant to any one of the depots; the vehicles then return to the plant to be refilled for the next delivery until all three depots are replenished.

7.3 Synchronizing production, inventory and routing

According to this model, the orders will be produced using the EDD algorithm, which takes into consideration the production capacity minimizing the setup costs every day.

The total distance delivered is shown in Figure (7.12), and the total distance is 5,854.3 km.

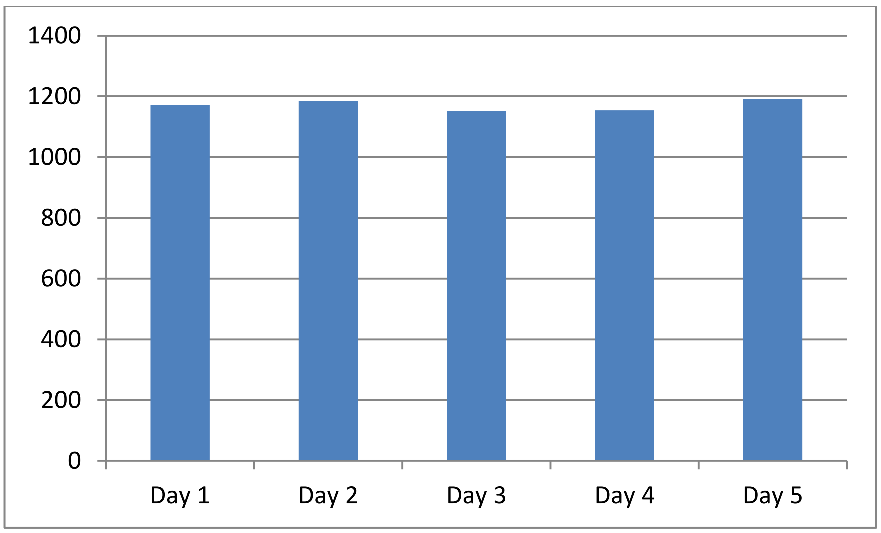


Figure (7.12): Total distance travelled

Figure (7.13) shows the routes, utilization and distances for day one.

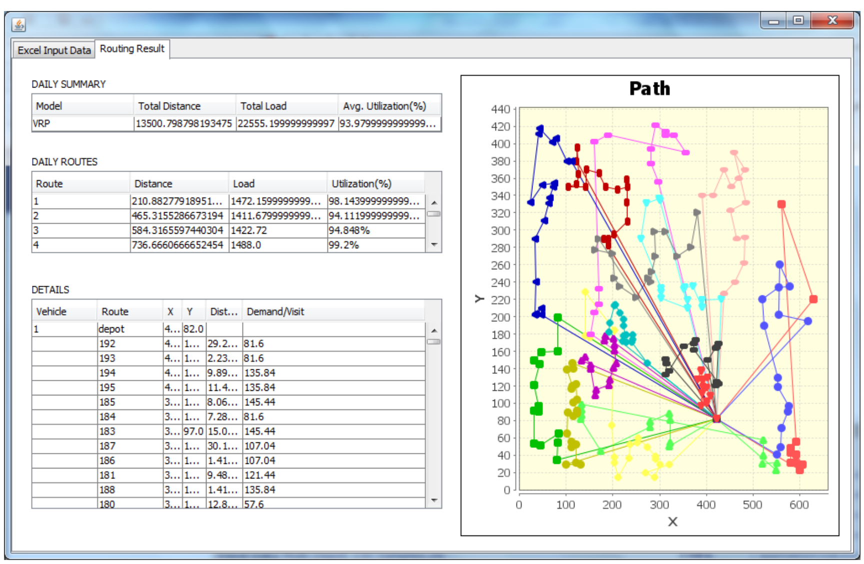


Fig. (7.13): Screen shot for routes, utilization and distance

The truck utilization is showed in Figure 7.14

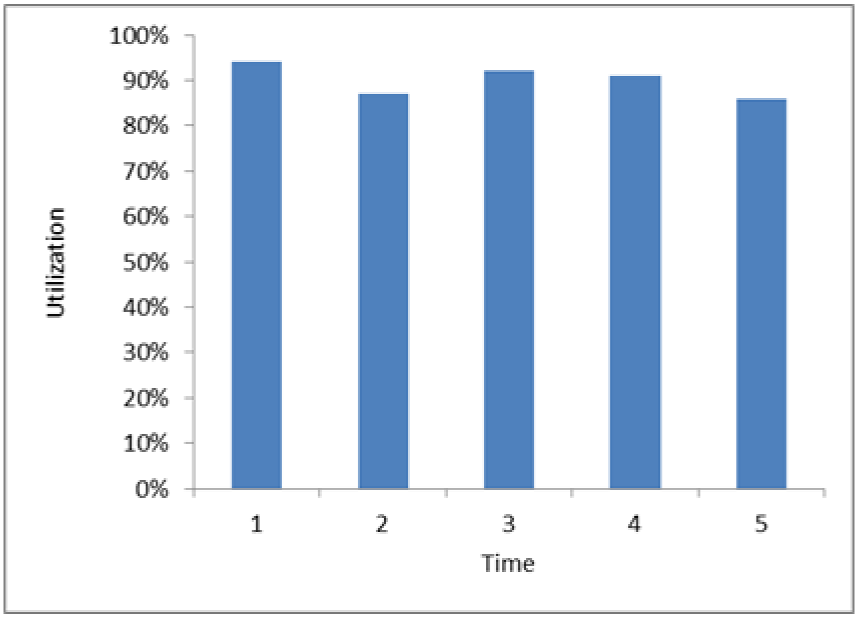


Fig. 7.14 Truck utilization

Figure 7.15 shows costs comparison between the three costs categories.

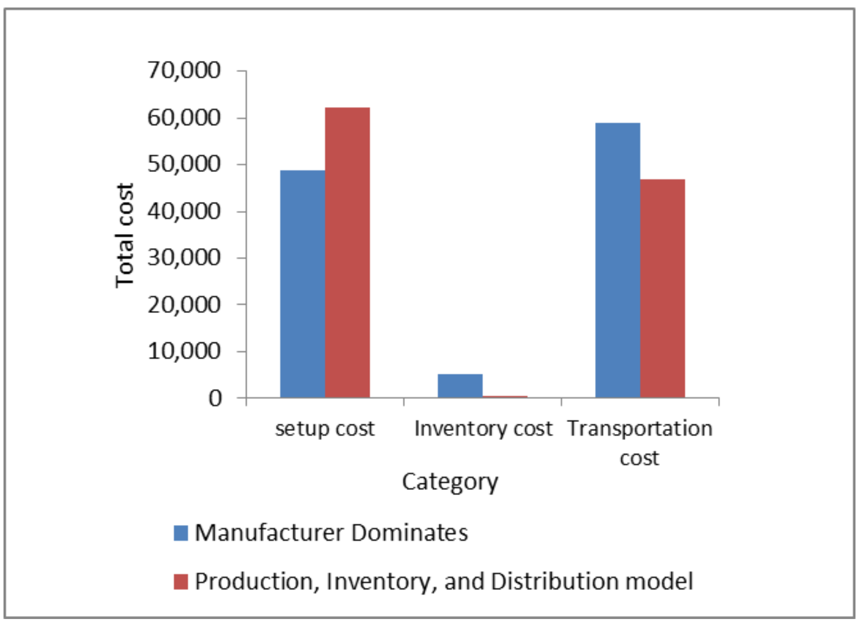


Fig. 7.15 Costs comparison of the two models

In this figure, it is clear that the setup costs will increase in the syncronizing model. This is due to the increase the number of setup times per one week. On the other side, the transportation and inventory costs will decrease. The total costs will decrease by 2.8%.

The reason for higher transportation cost, even with low fuel and transportation cost, is that the total travelled distance is high. The retailers are geographically dispersed. If the transporter goes to the most urgent retailer, it will usually go a further distance.

To analyze the effect of the transportation costs on the model, sensitivity analysis is carried out. This analysis aims to answer the question of how much the transportation cost can rise while still having the same total cost. The comparison is done with respect to the total travelled distance.

Figure 7.16 shows the results of the sensitivity analysis if the transportation cost is increased compared with the transportation distance.

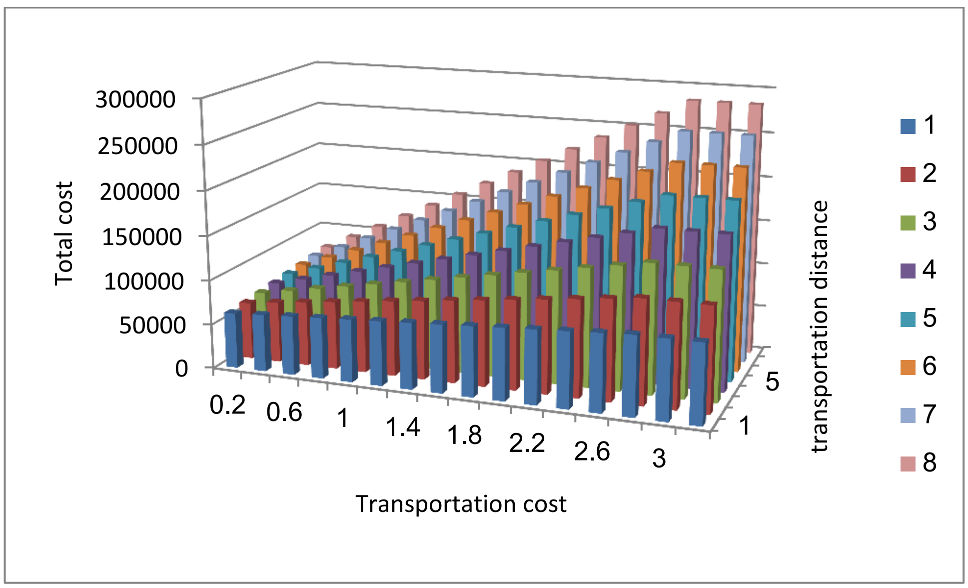


Figure 7.16 sensitivity analysis with transportation distance consideration

The first axis shows the total distance travelled (× 1,000 km); the second axis is the unit transportation cost per kilometer, while the third axis shows the total cost.

As shown in the figure, the effect of the transportation cost increases when the total travelled distance increases. For example, if the unit transportation cost increased to 3.2

the total distance should not exceed 1,600 km to have the same total cost obtained by the model.

It is clear from this figure that for shorter distances travelled (10,000 km) the effect of the transportation cost will be smaller than the same effect for the longest distance.

To decide which model (manufacturer dominates or synchronizing production, inventory and transportation) is best, this depends on the comparison of benefits of using one of the two models. To explain this, a benefit analysis will be provided. This analysis is a development of the cost conflict analysis obtained by Milid *et al*.[69]

Assume that:

σ^m: The manufacturer optimal schedule

σ^s: The supply chain optimal schedule

$\mu(\sigma^m)$: The inventory schedule according to σ^m

$\varepsilon(\sigma^m)$: The transportation schedule according to σ^m

α, β are parameters where $0 \leq \alpha \leq 1$, and $0 \leq \beta \leq 1, \alpha + \beta \leq 1$

The objective function is to minimize the total cost (of setup, inventory, and transportation costs).

When manufacturer dominates:

$$\text{Total cost} = TC^{MD} = \alpha\ T(\sigma^m) + \beta\ T\big(\sigma^m, \tau(\sigma^m)\big) + (1 - \alpha - \beta)\ T(\sigma^m, \rho(\sigma^m))$$

Where:

MD: manufacturer dominates, SY: synchronizing production, inventory and transportation

$T(\sigma^m)$: setup cost when considering the optimal manufacturer schedule.

$T\big(\sigma^m, \tau(\sigma^m)\big)$: inventory cost when considering the optimal manufacturer schedule.

$T(\sigma^m, \rho(\sigma^m))$: transportation cost when considering the optimal manufacturer schedule.

σ^s: synchronizing production, inventory and transportation schedule

When synchronizing production, inventory and transportation

$$\text{Total cost} = TC^{SY} = \propto \sigma^s + \beta\, T\big(\sigma^s, \tau(\sigma^s)\big) + (1-\alpha-\beta)\, T(\sigma^s, \rho(\sigma^s))$$

$$\text{The benefit of synchronization} = (TC^{MD} - TC^{SY})/TC^{MD}$$

assume that: $\propto = \{0.1, 0.3, 0.5, 0.7, 0.9\}$, and $\beta = 0.1$

Table (7.12) shows the cost of setup, inventory and transportation at deferent values of α. It is clear that when α arises the setup cost will also arises.

Table (7.12) total cost at different values of α when manufacturer dominates

	setup	inventory	transportation	Total
α=.1	4875	525	47072	52472
α=.3	14625	525	35304	50454
α=.5	24375	525	23536	48436
α=.7	34125	525	11768	46418
α=.9	43875	525	0	44400

Table (7.13) total cost at different values of α when synchronizing production, inventory and transportation

	setup	inventory	transportation	Total
α=.1	6225	60	37465.6	43750.6
α=.3	18675	60	28099.2	46834.2
α=.5	31125	60	18732.8	49917.8
α=.7	43575	60	9366.4	53001.4
α=.9	56025	60	0	56085

Table (7.14) shows the benefit of using the manufacturer schedule. It shows that at lower values of α (which means that lower values of setup cost), it is better to use the synchronizing model, which reduces the total cost by 16.6%. For α greater than 0.4, it is better to use the manufacturer schedule. That is because it has the higher effect on the total cost.

Table (7.14) The benefit cost

α	0.1	0.3	0.5	0.7	0.9
	16.6%	7.2%	-3.0%	-14.2%	-26.3%

As shown in Figure (7.17), when α is greater than 0.4 the benefit of using the synchronized model is less than zero. That means the manufacturer prefers his own schedule than the synchronized schedule.

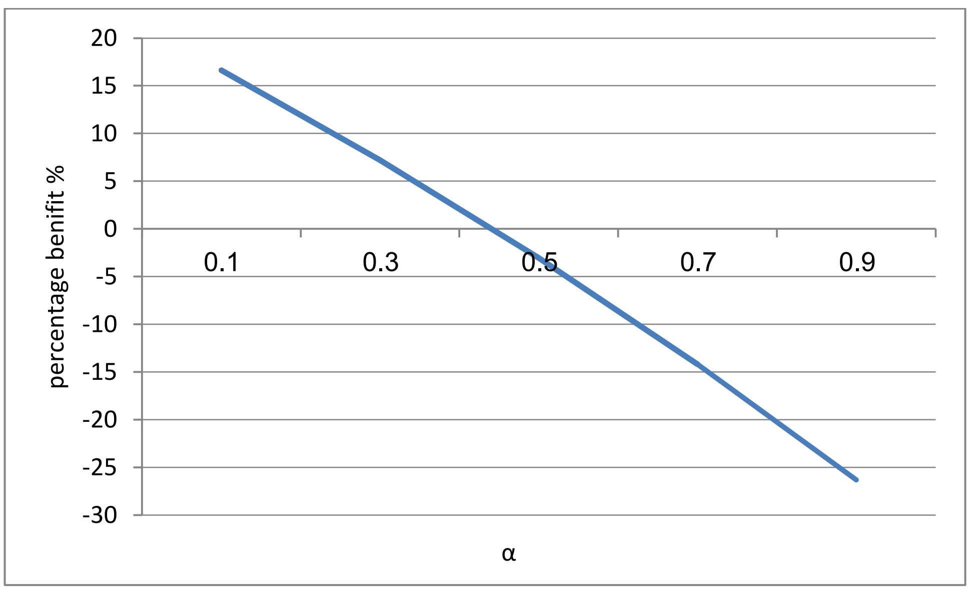


Figure (7.17) benefit cost

The same analysis could be done for the the inventory-dominated model or the distributor-dominated model. In these cases, the manufacturer will make his schedule according to the distributor (or inventory) optimum schedule.

Conclusions and future work

The primary objective of this research was to determine the effect of synchronizing the functions at different stages of a supply chain, to minimize production, inventory, and transportation costs. This work studied two scenarios of problems for a three-echelon supply-chain problem: (1) manufacturer dominated: where the manufacturer obtains his optimum job schedule and then the distributor tries to find his optimum schedule according to it, and (2) synchronizing production, inventory and transportation problems, with the aim of minimizing the total costs.

As a conclusion, the main contribution of this thesis is to propose a heuristic approach to deal with the PID problem in an environment with one plant, multiple depots, and multiple retailers. The proposed approach considers the setup time at the production line. In addition, the proposed algorithm considers the optimal transportation routes.

In almost all existing literatures regarding the studies on both PID and vendor-managed inventory (VMI) problems, just one product is considered. However, in reality, the plants produce more than one product. In addition, many literatures do not consider the routes problem. Moreover, machine setup time is also ignored. However, machine setup time is inevitable in practice.

In this thesis the concept of a VMI problem, replenishment policy and the vehicle routing problem model were studied and integrated to solve the three-echelon distribution problem of a single-plant, multi-depots, multi-retailers environment. Many previous studies failed to consider both the inventory problem and the transportation problem together based on three levels with multiple items. Some researches considered only the inventory problem for one depot and multi-retailers distribution system, while other researches only studied vehicle routing problems, which are all based on a two-level problem. Integrating the inventory problem and vehicle routing problem can solve the 1-M-M distribution system with different approaches taken from the existing models. However, the solutions to the distribution system shown by applying the developed models are not always optimal solutions. The solutions depend on the conditions of all factors involved in the system.

According to the developed models, retailers and depots are first grouped into various clusters according to the consumption rate and capacity through the nearest neighbour and stem distance algorithms. Basically the route-first, cluster-second approach is applied to supply retailers. After all the retailers are routed, a specific service sequence list for each cluster is created based on the urgency of each retailer. Then several routes are assigned according to the service sequence list. Two scenarios were investigated in the VMI model. The first one is a one-product one-truck scenario, and the second one is a multi-products one-truck scenario. The results shows that the second scenario was better. An insertion heuristic has been brought in as an improvement based on scenario 2 with the objective of ultilizing vehicle capacity without increasing total cost, which is finally proven to show significant progress in the study. Therefore when a company has to decide when and how much to replenish customers, these scenarios might provide directions to make decisions.

The second main model involved synchronizing production, inventory and transportation. In this model the setup costs increased, but the inventory and transportation costs were decreased. Comparing the two models showed that the total costs were decreased when the synchronized model was applied.

The benefit of using each model depends on the weight of each cost part (setup, inventory and transportation costs). For higher values of setup cost, it is better to use the manufacturer-dominated model.

There are several potential extensions from this work. First, from a practical point of view, other job scheduling models (such as job shop or parallel machines) could be investigated. Also, models containing more than one plant that produce the same products which can delivered to the same retailers could be considered. In the latter case the setup cost could be minimized while the transportation cost could be increased.

Second, from a research point of view, new algorithms that can effectively solve the integrated production, inventory and distribution-routing problem of setup time could be suggested. Also, the idea of impeding products and customers could be further improved to reduce the transportation cost.

Appendices

Appendix I setup time matrix (in minutes) at packing machine.

Brand	1			2		3		4	
Den.	E_1	E_2	E_{10}	E_1	E_2	E_1	E_2	E_1	E_2
Pr. No.	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	-	30	90	10	30	10	30	10	30
P_2	30	-	90	30	10	30	10	30	10
P_3	90	90	-	90	90	90	90	90	90
P_4	10	30	90	-	30	10	30	10	30
P_5	30	10	90	30	-	30	10	30	10
P_6	10	30	90	10	30	-	30	10	30
P_7	30	10	90	30	10	30	-	30	10
P_8	10	30	90	10	30	10	30	-	30
P_9	30	10	90	30	10	30	10	30	-

Appendix II setup time matrix (in minutes) at drying stage.

Brand	1			2		3		4	
Den.	E_1	E_2	E_{10}	E_1	E_2	E_1	E_2	E_1	E_2
Pr. No.	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
P_1	-	-	60	60	60	60	60	60	60
P_2	-	-	60	60	60	60	60	60	60
P_3	60	60	-	60	60	60	60	60	60
P_4	60	60	60	-	-	60	60	60	60
P_5	60	60	60	-	-	60	60	60	60
P_6	60	60	60	60	60	-	-	60	60
P_7	60	60	60	60	60	-	-	60	60
P_8	60	60	60	60	60	60	60	-	-
P_9	60	60	60	60	60	60	60	-	-

Appendix III: Randomly generated algorithm

- *Initialization*

  Enter the number n of jobs.

  For each job, enter its processing time P_j and its release date r_j.

  Read setup times s_{jk} for each pair of jobs j and k, with j =1= k.

  Define the number of iterations (niter).

- *Algorithm*

  1. Set h = 1, the first iteration. Set j = 1.

  2. Generate an integer random number R from an equilikely distribution between 1 and n.

  3. Schedule job j on position defined by R. If this position is already assigned, go to step 2.

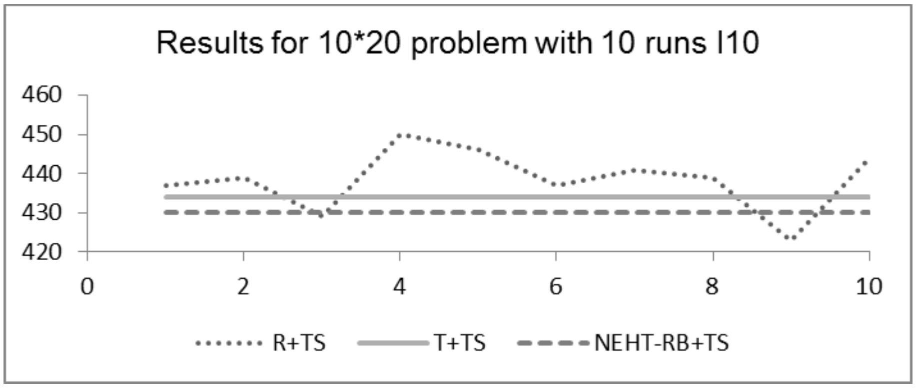
  4. Do j = j +1 and repeat from step 2 while j ::; n (that is, until all jobs are scheduled).

  5. Ensuring that release dates are respected, compute Cmax, the make span for the schedule of iteration h.

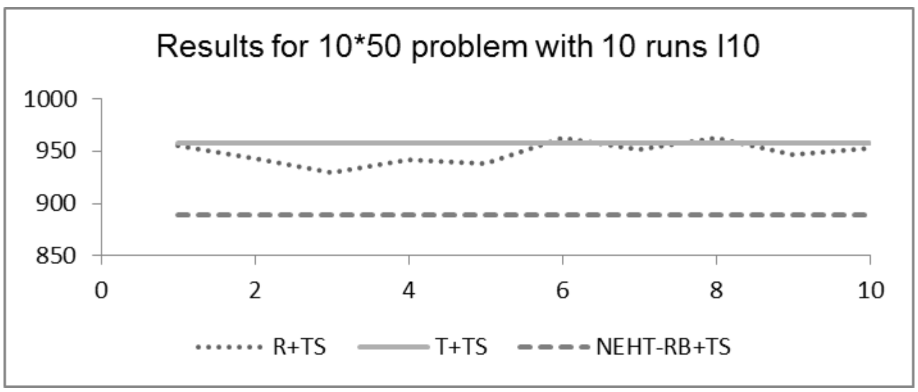
  6. Do h = h +1 and repeat from step 2 while h ::; niter (that is, until the number of iterations is reached).

  7. Select the schedule with mi n_j, Cmax (that is, select the schedule with minimum make span over all the iterations).

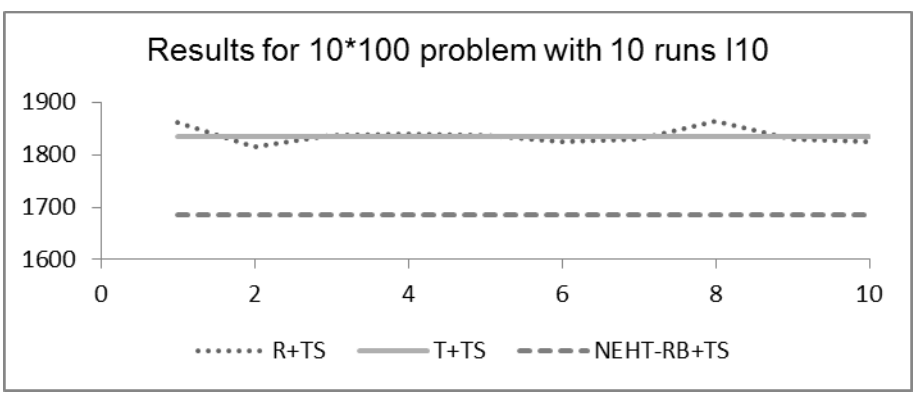
Appendix IV: Comparison results of NEH, randomized and SP algorithms.



(a) Results for 10*20 problems with 10 runs



(b) Results for 10*50 problems with 10 runs



(c) Results for 10*100 problems with 10 runs

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Curriculum Vitae

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