Optimal Inventory Control and Distribution Network Design of Multi-Echelon Supply Chains

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Abstract

Today, most companies have more complex supply chain networks in a more volatile business environment due to global sourcing, outsourcing of production and serving customers all over the world with a complex distribution network that has several facilities linked by various activities. More companies involved within the value chain, means more nodes and links in the network. Therefore, globalization brings complexities and new challenges as enterprises increasingly benefit from global supply chains. In such a business environment, Supply Chain (SC) members must focus on the efficient management and coordination of material flow in the multi-echelon system to handle with these challenges. In many cases, the supply chain of a company includes various decisions at different planning levels, such as facility location, inventory and transportation. Each of these decisions plays a significant role in the overall performance and the relationship between them cannot be ignored. However, these decisions have been mostly studied individually. In recent years, numerous studies have emphasized the importance of integrating the decisions involved in supply chains. In this context, facility location, inventory and transportation decisions should be jointly considered in an optimization problem of distribution network design to produce more accurate results for the whole system. Furthermore, effective management of material flow across a supply chain is a difficult problem due to the dynamic environment with multiple objectives. In the past, the majority of the solution approaches used to solve multi-echelon supply chain problems were based on conventional methods using analytical techniques. However, they are insufficient to cope with the SC dynamics because of the inability to handle to the complex interactions between the SC members and to represent stochastic behaviors existing in many real world problems. Simulation modeling has recently become a major tool since an analytical model is unable to formulate a system that is subject to both variability and complexity. However, simulations require extensive runtime to evaluate many feasible solutions and to find the optimal one for a defined problem. To deal with this problem, simulation model needs to be integrated in optimization algorithms.

In response to the aforementioned challenges, one of the primary objectives of this thesis is to propose a model and solution method for the optimal distribution network design of an integrated supply chain that takes into account the relationship between decisions at the different levels of planning horizon. The problem is formulated with objective functions to maximize the customer coverage or minimize the maximal distance from the facilities to the demand points and minimize the total cost. In order to find optimal number, capacity and location of facilities, the Nondominated Sorting Genetic Algorithm II (NSGA-II) and Quantum-based Particle Swarm Optimization Algorithm (QPSO) are employed for solving this multiobjective optimization problem. Due to the complexities of multi-echelon system and the underlying uncertainty, optimizing inventories across the supply chain has become other major challenge to reduce the cost and to meet service requirements. In this context, the other aim of this thesis is to present a simulation-based optimization framework, in which the simulation is developed based on the object-oriented programming and the optimization utilizes multi-objective metaheuristic techniques, such as the well-known NSGA-II and MOPSO. In particular, the proposed framework suggests a great utility for the inventory optimization problem in multi-echelon supply chains, as well as for other logistics-related problems.

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Abbreviation

ABS	Agent-Based Simulation
APS	Advanced Planning Systems
CD	Coverage Distance
CFLP	Capacitated Facility Location Problem
CV	Coefficient Of Variation
DCs	Distribution Centers
DES	Discrete-Event Simulation
FIFO	First In-First Out
FTL	Full Truckload
GA	Genetic Algorithm
LIFO	Last In-Last Out
LTL	Less-Than-Truckload
MILP	Mixed Integer Linear Programming
MMP	Multi-Site Master Planning
MOPSO	Multiobjective Particle Swarm Optimization
MOPSO-SO	Simulation-Based Optimization Based On MOPSO
MTS	Make-To-Stock
NP	Non-Deterministic Polynomial-Time
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NSGA-II-SO	Simulation-Based Optimization Based On NSGA-II
OOB	Object Oriented Programming
PSO	Particle Swarm Optimization
QPSO	Quantum-Based Particle Swarm Optimization
RMS	Response Surface Methodology
SBO	Simulation-Based Optimization
SC	Supply Chain
SCM	Supply Chain Management
SCP	Set Covering Problem
SD	System Dynamics
SND	Strategic Network Design
TSP	Travelling Salesman Problem
VRP	Vehicle Routing Problem
WR	Warehouse

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Chapter 1

Introduction

1.1 Background and Motivation

Increased competition, globalization in today's market, products with shorter life cycles, and the high level of customer service have forced businesses to invest in, and focus attention, on their supply chains (Simchi-Levi et al., 2004). Generally, a supply chain (SC) is referred to as a network of facilities and business activities consisting of the design of new products, procurement of raw materials, transformation of such materials into semi-finished and finished products, and delivery of such products to the end customer. This definition, or a modified version of it, has been used by several researchers (see (Lee & Billington, 1993), (Swaminathan et al., 1998), and (Ganeshan & Harrison, 1995)). Companies face a set of supply chain challenges due to some kind of uncertainty and variability. Today, most companies source globally, produce in various plants and serve customers dispersed over a large geography with a complex distribution network which has several stock points linked by various activities. This increase in globalization brings new challenges as well benefits. Decisions along a supply chain that should be coordinated contribute to the complexity of global logistic networks. In response to these challenges, companies need efficient approaches and methods helping in addressing uncertainty in their distribution network and validating their decisions that lead to achieve their objectives.

The current trend in logistics is supply chain management (SCM) concerned with the coordination and synchronization of the material, informational and financial flows in a distribution network (Chopra & Meindl, 2004). Due to the growing complexity of these networks and rapid development of new technologies to manage them, interest in SCM has grown among both academicians and the practitioners over the last decades. One major issue of SCM is to find the best possible network configuration so that organizations can achieve effective and efficient logistics operations that improve the performance of the company. This objective supports integrating facility location with different supply chain processes such as procurement, production, inventory, distribution, and transportation (Melo et al., 2008).

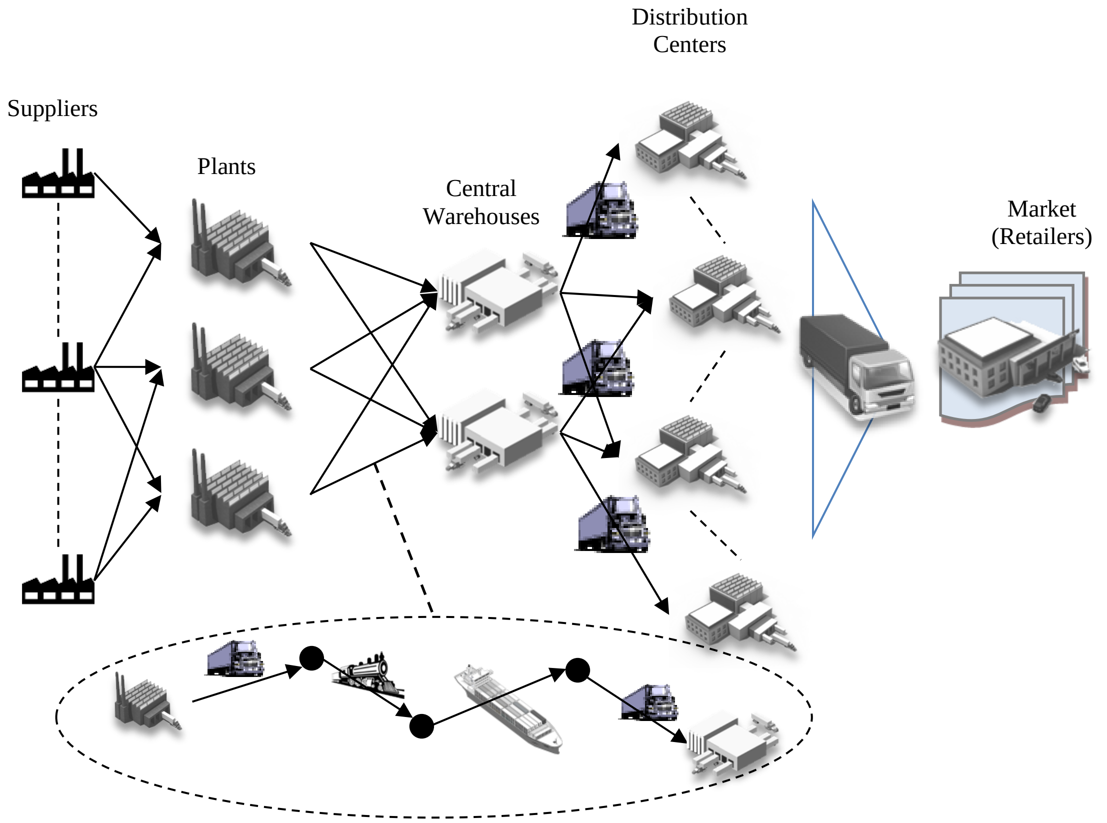


Figure 1-1: Structure of a typical multi-echelon supply chain (Ghiani et al., 2004)

If an item moves through more than one step before reaching the final customer, the supply chain is called multi-echelon or a multi-level production/distribution system (Chopra & Meindl, 2004). Figure 1-1 shows the structure of a typical multi-echelon supply chain. Although managing information and material flow in a global logistic system can be challenging, companies that learn how to design and manage their complex distribution network will have a substantial competitive advantage in their markets (Hugos, 2003). Reconfiguring the network of a supply channel can result in a logistics cost reduction of 5 to 15% while maintaining or improving customer service (Ballou, 2001). When solving such problems, a firm may have to determine optimal facility locations and their size, the transportation links among the members of the supply chain, and customer assignment to the selected facilities (Correia et al., 2012). Moreover, those companies are faced with some additional decisions that arise in designing logistics networks, such as determining how much inventory a facility should carry and when orders should be made (Ma, 2003).

There are alternative approaches to solve the facility location problem. Traditionally in Operational Research, analyses of different locations can be formulated based on two philosophies: all geographical points on a 2-dimensional plane are possible facility locations, or discrete location alternatives are given as a finite set. These models for finding optimal configurations are optimized by standard integer programming or network optimization techniques whose aim is to minimize total cost or maximize profit. However, in practice, facility location decisions often have multiple objectives that can add or reduce value to a potential configuration in the location choice (Daskin, 1995). In the multiobjective network design, the basic problem is to construct a network optimally that satisfies the system's additional constraints, such as space constraints, coverage distance, and time limits. In the case of more complex models with further constraints, more powerful solution techniques may be required. Furthermore, in recent years, numerous studies have emphasized the importance of integration of supply chain decisions for the distribution network design ((Shen et al., 2003), (Daskin et al., 2002), (Shen & Qi, 2007)). Under this framework, the facility location, inventory and transportation costs are jointly considered in an optimization problem in order to have more accurate results for the whole system. Research in this vein underlines that ignoring the interdependency between these decisions can lead to suboptimal solution in the network design problem (Shen & Qi, 2007).

Supply chain network design is often difficult to analyze due to complex supplier relationships, the coordination of numerous business processes, uncertainty in production and delivery, the complexity of modeling the individual entities, and the stochastic nature of demands. In the literature, many models have been formulated based on quantitative techniques for the improvement and optimization of SCs like linear programming, differentiation, and local gradient-based methods. Mixed integer linear programming (MILP) is the most widely used technique. The interested reader can refer to survey papers by Meixell and Gargeta (2005), and Vidaland and Goetschalckx (1997). However, due to the high complexity and difficulty of real world problems, these methods are usually not sufficient owing to the fact that most of the supply chain models are discrete, non-linear and multi-modal (Silva et al., 2009). In addition, traditional exact methods need very high computational time to find the optimal solution for very large scale problems. Therefore, in recent years, metaheuristic algorithms such as Evolutionary Computation (EC), Simulated Annealing (SA), Tabu Search (TS), Particle Swarm Optimization (PSO), and others have been applied to various optimization problems as successful alternatives to classical techniques (Silva et al., 2003) (Altiparmak et al., 2006).

Two modeling approaches are widely used to evaluate the performance of such systems: simulation techniques and analytical modeling (Svensson, 1996). The operations research community also uses mathematical programming techniques (also called analytical or optimization techniques) such as Linear Programming and Mixed Integer Programming to formulate solutions to supply chain problems. However, these techniques are not able to deal efficiently with the uncertainty and SC dynamics because of their inability to represent stochastic behaviors or highly complex relations between the different entities existing in real-world problems (Mele et al., 2006). Unlike the traditional analytical methods, researchers also use simulation as a decision support tool to analyze the overall performance of a system without limiting assumptions. Since it can model the compound effects of uncertainty and non-linear relations in the system, the simulation model is normally preferable when an analytical model is not be able to formulate the system that is subject to both variability and complexity. However, simulation provides no concrete solutions to optimization problems, and users need to evaluate many feasible solutions in order to find an optimal solution to a problem (Güller et al., 2015). Thus researchers have attempted to combine simulation and optimization procedure. This approach is called simulation-optimization or simulation-based optimization. Simulation-based optimization (SBO) can be defined as the process of finding the best input variable values from among all possibilities without explicitly evaluating each possibility and integrating optimization techniques into simulation where the simulation model is regarded as the evaluation mechanism (Carson & Maria, 1997).

1.2 Decision Levels in Supply Chains

Planning processes of a SC are divided into three levels in terms of planning horizon: strategic level, tactical level and operational level (see Figure 1-2) (Chopra & Meindl, 2004). Designing the distribution network in an optimal way is at the core of strategic planning in supply chain management (SCM) and crucial for firms. According to Harrison (2005), up to 80% of the total cost of a product is driven by network design decisions. Furthermore, companies need to improve their network strategy in order to be more responsive to customer demand in today's highly dynamic and competitive environment. This issue involves a number of questions to be addressed (Jayaraman, 1998):

- How many facilities should be sited?
- Where should each facility be located?
- How should customer demand be allocated to each facility?

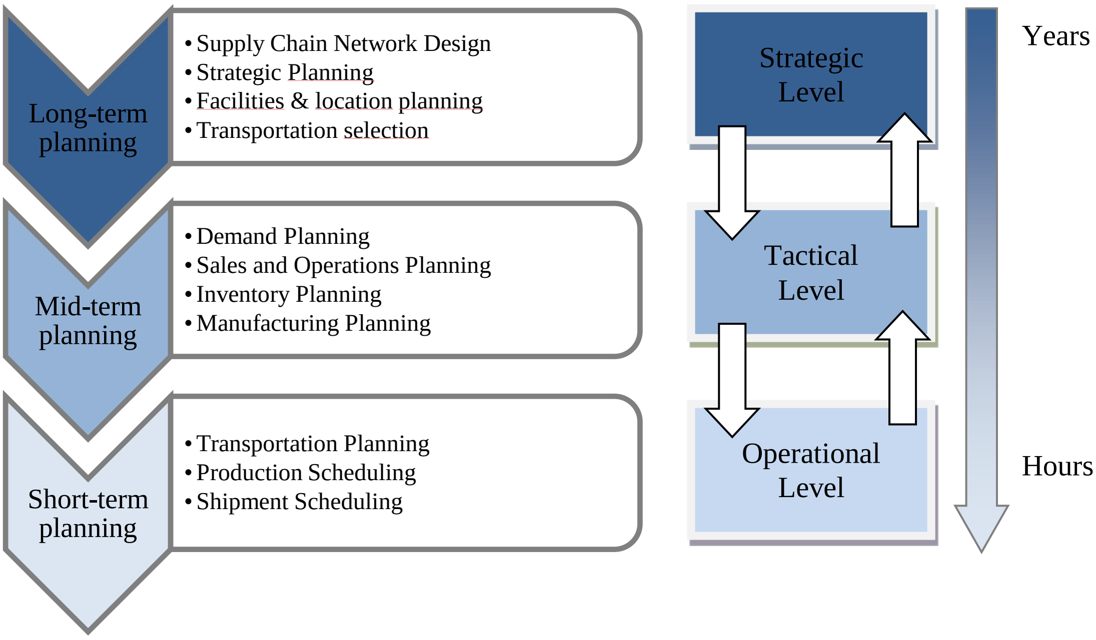


Figure 1-2: The hierarchical framework of supply chain planning tasks (Rushton et al., 2010)

The mid-term planning level (also called tactical decisions) deals with resource allocation and measuring performance against specified targets in order to achieve results outlined at the strategic level (Gunasekaran et al., 2004). The scope of the planning horizon is between 6 and 24 months (Rushton et al., 2010) (Silver et al., 1998). The most significant decisions to be made at this level are inventory control parameters, production and distribution coordination, order and freight consolidation, and delivery frequencies to customers. At this decision level, decision makers often face difficulty in finding the appropriate inventory level at each stage of a supply chain. Moreover, the difficulty increases in multi-echelon systems due to the stochastic nature of the demand, capacity, and lead time, as well as the complex interaction of ordering decisions between different stages and the dynamic interconnection of supply chain members. The objective of multi-echelon inventory management is often defined in terms of minimizing the inventory level of the system to decrease the total inventory cost while meeting the end customers' service requirements.

At the lowest planning level, all operations are required to ensure that the system continues to function towards its goal as specified and scheduled. The planning horizon at this level is typically one week, and decisions deal with operational routines such as workforce scheduling, vehicle routing and scheduling, material replenishment, and packaging (Azambuja & O'Brien, 2008). These decisions obviously affect the distribution strategy and transportation cost. Transportation and inventory costs constitute the largest proportion of the total supply chain cost (Ballou, 2004). Based on estimates for the U.S. in 2002, transportation costs were $577 billion, and inventory carrying costs and warehousing costs were $298 billion. The total logistics costs were $910 billion, which was equivalent to 8.7% of the U.S. gross domestic product in 2002 (Akca, 2010).

The right combination of these decisions is vital for the optimization of overall supply chain performance. Traditionally, most approaches to supply chain network optimization in the literature consider decisions at different levels separately. For example, most of the optimization models concerning the configuration of the supply chain network focus their attention on trade-offs between transportation and fixed facility costs, disregarding inventory control decisions (Daskin, 1995). On the other hand, inventory decisions are optimized to balance the trade-off between inventory holding and fixed replenishment costs under a fixed supply chain network structure. However, there is a clear relationship between the inventory cost, transportation cost and the supply chain's physical structure. This highlights a need for models that integrates strategic, tactical and operational decisions, known as an integrated supply chain design.

1.3 Integrated Supply Chain Network Design

Integration of the decision levels can be useful for different aspects of a company's supply chain. According to Shapiro (2001), there are three dimensions to integration.

a) Functional integration is concerned with purchasing, manufacturing, warehousing, and distribution activities within the company, and between the company and its suppliers and customers.
b) Spatial integration is done over a target group of supply chain entities – vendors, manufacturing facilities, warehouses, and markets.
c) Inter-temporal integration refers to integration of the overlapping decisions in the strategic, tactical and operational planning horizons.

Goetschalckx and Fleischmann (2005) describe two key planning decisions for network design. These decisions are i) status of a particular facility or manufacturing line and relationships or allocations during a specific planning period and ii) the product flows and storage quantities (inventory) in the supply chain during a planning period.

Planning decisions of the strategic network design have both interrelated spatial and temporal characteristics. However, the planning and integration of decisions along a supply chain are difficult and complex tasks. Advanced Planning Systems (APS) can be used as a tool in order to provide reliable supply chain planning. APS is described as a decision support system that uses advanced optimization techniques and a planning matrix that decomposes the planning functions into the commonly used software modules. Furthermore, it introduces a hierarchical integration of different decision among various supply chain operations (Meyr et al., 2008). Figure 1-3 shows the interaction among value chains for optimizing a supply chain by using APS. APS uses advanced mathematical algorithms (e.g., genetic algorithms, linear programming, etc.) in order to provide nearly optimal solutions for supply chain planning issues (Selcuk, 2007). These algorithms simultaneously consider a range of constraints to perform the optimization.

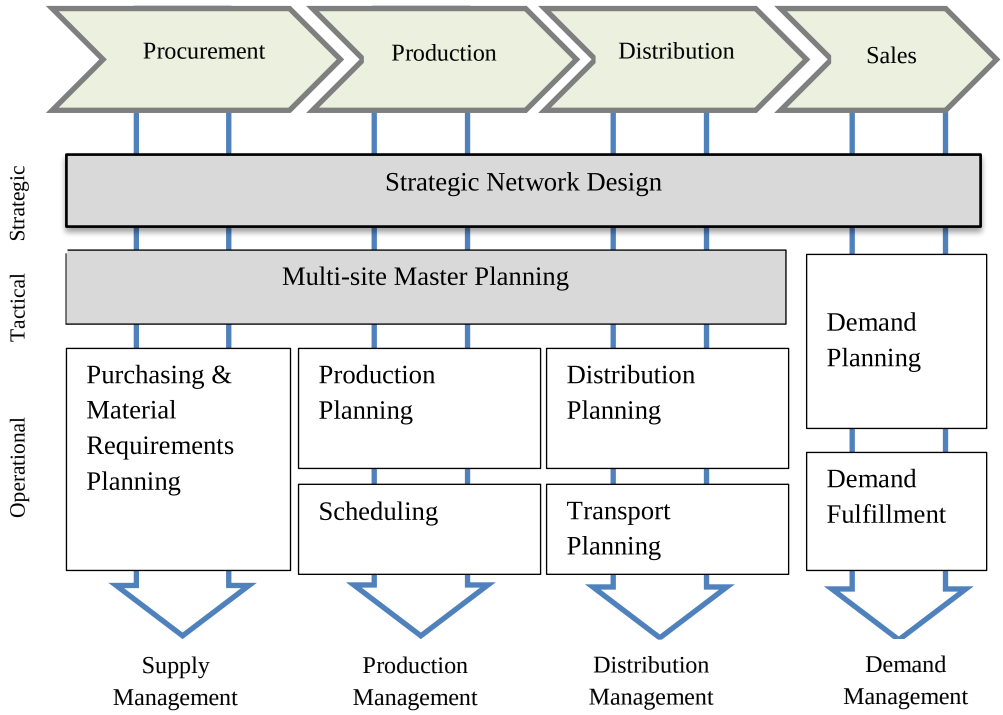


Figure 1-3: Typical APS modules covering the SCM matrix (Meyr et al., 2008)

This dissertation focuses on the strategic and tactical levels, i.e. strategic network design (SND) module and multi-site master planning (MMP) module as shown in Figure 1-3. The SND module determines the number of plants and distribution centers, their location and capacity, and the assignment of customers to each facility in the supply chain, as well as possible distribution channels as described in the previous section (Jonsson & Kjellsdotter, 2007). The Master Planning module synchronizes the flow of materials along the entire supply chain and coordinates production, transportation, supply capacities, and seasonal stock. It also balances supply and demand. The decisions on production, inventory and transport quantities need to be addressed simultaneously (Jens & Michael, 2005). As a result of this synchronization, production and transportation entities are able to reduce the inventory level at stock points.

Combining the relevant decisions that arise at the strategic, tactical and operational levels, one must consider all relevant costs including location, inventory and transportation costs in an integrated system. These three costs are highly related and, ideally, should be considered jointly when making network design decisions (Daskin et al., 2005). For example, a high number of distribution centers (DCs) reduces the cost of transporting product to retailers and ensures better service. However, under this model pooling effects increase the cost of holding inventory and increase the fixed costs associated with operating DCs (Erlebacher & Meller, 2000). The challenge is to find the right balance between installation DCs, inventory, and transportation costs that achieves customer service goals at the minimum total system-wide cost. Once the supply chain network is determined, the focus shifts to decisions at the Master Planning module (Shen, 2005). One of the major decisions related to the Master Planning module is inventory control. In this module, the goal is to determine the optimal number of shipments, shipment sizes, and inventory and transportation costs (Meyr et al., 2008).

1.4 Research Questions and Objectives of the Dissertation

Although there has been tremendous interest in supply chain design and inventory management for decades, the research on integrated approaches is quite scarce. Most practical optimization problems involve multiple and conflicting objectives that must be optimized simultaneously. Furthermore, uncertainty in demand and cost parameters is other factor that can contribute to the complexity of location/inventory problem and influence the effectiveness and responsiveness of the logistic network. In this context, the primary objective of this dissertation is firstly to propose a model and solution method for the optimal distribution network design of an integrated supply chain that takes into account the relationship between decisions at the different levels of planning horizon. The other purpose of the dissertation is to provide a modeling framework that integrates simulation models and multiobjective optimization methods to find the optimal inventory allocation policy for each facility in the supply chain under a stochastic environment. More specifically, this research proposes two multiobjective metaheuristic optimization algorithms that find Pareto optimal solutions to the facility location problem and the multi echelon inventory allocation problem.

The objectives of this research are:

- To define and formulate a general methodology for an integrated supply chain network design in order to analyze the interactions between the planning decisions at different levels. This thesis presents a model to support strategic network design as well as two metaheuristics for solving the integrated facility location problem with multiple objectives. Specifically, it analyzes the impact of integrated decision-making on overall cost, facility location decisions, and customer service level in terms of coverage distance.
- To establish an experimental simulation environment (i.e., library using C-Sharp) for multi echelon system to investigate the impact of operational decisions on the performance and to address the stochastic nature of business environments. The proposed framework provides a flexibility allowing for quick modifications to research measures, such as the comparison of inventory policies, stochastic behavior of the supply chain variables, safety stock evaluations, and the effect of different inventory control parameters.
- To develop a simulation-based inventory optimization framework, in which the simulation is developed based on the object-oriented programming and the optimization utilizes multi-objective metaheuristic techniques. For multi-objective optimization, two sets of objectives are defined for the inventory problem, i.e., the system wide cost and the customer service level. Two metaheuristic techniques are tested and analyzed as an optimization algorithm to find the best inventory control parameters.
- To investigate the performance of metaheuristic techniques – particularly their ability to handle constraints – with the empirical study of multi-objective optimization techniques. Specifically, this dissertation compares the performance of existing algorithms NSGA-II and MOPSO based on computational time and convergence.

1.5 Outline of Thesis

Chapter 2 provides a brief overview of the existing literatures in the fields of integrated supply chain network design, multi-echelon inventory control, and applied metaheuristic approaches. This chapter also surveys relevant literatures in the methodology of simulation on inventory control and simulation-based optimization.

Chapter 3 introduces the basic concepts of metaheuristic techniques and different multiobjective optimization methods that are used to find Pareto optimal solutions. This work is mostly based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The chapter also presents a brief introduction to Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO).

Chapter 4 presents the integrated distribution network design model for the food industry in detail and explains the solution technique using discrete metaheuristic optimization techniques. In this chapter, we present the problem statement and the mathematical formulation of the proposed integrated model. In this research we will apply the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Quantum-based Multiobjective Particle Swarm Optimization to approximate the Pareto front to generate valid solutions for the network design problem. The applicability of the proposed algorithm and the efficiency of the proposed integrated approach are presented in a computational experiment for a large-scale network involving several factories' warehouses, regional distribution centers and customers. To analyze the impact of optimization algorithm parameters and supply chain cost parameters, we empirically compare solutions over several variations.

Chapter 5 discusses the framework architecture of the simulation model and the detailed structure of each individual package through a simplified model of inventory in a multi-echelon supply chain. It discusses the development and implementation of an object-oriented simulation package.

Chapter 6 contains a brief description of the assumptions made during the simulations and experiments: in other words, input and output parameters of the simulation tool. The supply chain models that represent different inventory coordination mechanisms are developed and analyzed to compare their performances.

Chapter 7 describes the methodology of simulation-based multi-objective optimization, which integrates the optimization tool into the simulation, and the simulation model is regarded as an objective function. After introducing the proposed optimization concepts for the stochastic inventory problem, the chapter presents several numerical examples. It compares different evolutionary approaches, such as NSGA-II and MOPSO, due to their ability to lead to efficient generation of Pareto sets and computational time.

Chapter 8 concludes the thesis by summarizing the main development, major contributions, and limitations of this study. Possible directions for further research and indications for potential applications are offered as well.

Chapter 2

Literature Review

This literature review is divided into three sections: integrated supply chain network design, multi-echelon inventory system, and supply chain optimization models based on metaheuristic techniques. The review of integrated supply chain network design includes the models and algorithms of network design in an integrated environment and facility location problems, while the review of supply chain optimization models focuses on the metaheuristic techniques for global supply chain design and planning.

2.1 Literature Review on Integrated Supply Chain Network Design

In general, the classical facility location problem is concerned with selecting sites to install facilities and assign customers to these facilities in a way that minimizes the fixed facility location and transportation costs as well as all other relevant expenses. Shen (2007), (Daskin et al., 2002), Snyder (2007) and Melo et al. (2008) offer a comprehensive review in the research area of supply chain design. There are several papers in the area of integrated facility location and inventory control. Nozick et al. (1998) present a linear approximation to the total safety stock in terms of the function of the number of DCs. Nozick et al. (2001) extend their previous model by considering the service responsiveness and uncertainty in delivery time to the DC. The solution model consists of two sub-models. They first specify a minimum inventory level necessary to ensure a specified out-of-stock probability for a given product and propose an iterative updating scheme for solving optimal facility location. Shen et al. (2003) consider an integrated facility location/inventory location model to include nonlinear working inventory and safety stock costs for a two-stage network with multiple retailers under stochastic demand. The problem in their work is determining which retailers should serve as DCs and how much inventory these stocking points should hold. The model is initially formulated as a mixed integer nonlinear location allocation and solved with a column generation method.

The location-inventory problem has been solved widely by using Lagrangian relaxation based algorithms in literature ((Daskin et al., 2002), (Shen et al., 2003), (Snyder et al., 2007), (Miranda & Garrido, 2006)). Daskin et al. (2002) consider a model similar to the one addressed in Shen et al. (2003), where the model incorporates working inventory and safety stock inventory costs at the distribution centers. They formulated the model as a non-linear integer-programming problem with binary assignment variables, and propose a Lagrangian relaxation method for the case in which the ratio of the variance of demand at the retailers to the mean demand is the same for all retailers. Snyder et al. (2007) introduce the stochastic location model with risk pooling that optimizes location, inventory, and allocation decisions simultaneously. Miranda and Garrido (2006) also propose solution methods based on Lagrangian relaxation for mixed-integer nonlinear models. They consider the order quantity for each warehouse as a decision variable that they are trying to optimize. The variable is transformed into a series of Capacitated Facility Location Problem (CFLP) and proposed solution involves a Lagrangian relaxation and the sub-gradient method.

Erlebacher and Meller (2000) develop a non-linear integer inventory-location model for designing a two-level distribution system where customer demands are stochastic and rectilinear distances are used to represent the distances between the locations. The aim of their model is to decide on the number of distribution centers, their location and customer allocations that minimize the sum of the fixed operating costs of open DCs, inventory holding costs at DCs, total transportation costs from plants to DCs, and transportation costs from DCs to customers.

Recently, Shu et al. (2005) propose a two-stage stochastic model for the design of integrated supply chain network decisions related to strategic sourcing and distribution, warehouse-retailer assignment, and facility location in an integrated multi-echelon supply chain distribution network. They consider the joint replenishment of inventory at both warehouses' and retailers' level to minimize the total expected system-wide multi-echelon inventory, transportation, and facility location costs.

2.2 Literature Review on Multi Echelon Inventory System

Researchers have developed models to deal with a simplified single-vendor, single-buyer inventory problem. However, it is not practical for the supply chain network to have only one vendor and one buyer all the time in real-world business. The purpose of this section is to introduce the modeling philosophy and convention of the multi-echelon inventory studies under a continuous review system. For a recent overview, see e.g. Axsäter (2003).

A good review of the models dealing with continuous review policies for multi echelon inventory system can be found in Axsäter (1993). A well-known approach for multi-echelon inventory models is the METRIC method developed by Sherbrooke (1968). He describes a methodology for managing a two-echelon system for repairable items; however, the principles apply equally well to consumable items. The system consists of N identical retailers or bases at lower echelon and one warehouse at upper echelon that supplies the bases with repaired parts. It is assumed demand occurs only at the lower echelon and follows a simple Poisson process. All stock points apply a one-for-one replenishment control policy (S-1, S). In this case, the warehouse observes a Poisson demand process. The objective of the model is to identify stocking policies at the bases and the depot to minimize backorders at the base level subject to a constraint on the inventory investment. Later, Deuermeyer and Schwarz (1981) develop an inventory model for a two-echelon inventory system that consists of one warehouse and N identical retailers that implement (R, Q) policies. They present an approximate model to calculate the system service levels, and develop an optimization framework to maximize the system fill-rate subject to a system safety stock constraint.

De Bodt and Graves (1985) consider a multi-stage, serial inventory system under continuous review (Q, R) policy. They derive approximate performance measures with set-up cost under a nested policy assumption: whenever a stage receives a shipment, a batch must be immediately sent to its downstream stage. They do not make an assumption about the form of the demand distribution. In other words, the demand for the end item is stochastic and stationary.

Andersson and Marklund (2000) study decentralized inventory control in a two-level distribution system with a central warehouse and multiple non-identical retailers. In their model, all installations use continuous review installation stock (R, Q) policies. They present an approximate cost evaluation technique to minimize total inventory cost which also contains safety stock and backorder costs.

Hoque (2006) focuses on a two-echelon serial inventory system consisting of a warehouse and a retailer under constant demand. Each inventory location follows a continuous review (s, Q) policy, and unfilled demands are completely backordered on a first-come, first-served basis. He extended the existing model by taking into account the transportation time of a batch. Mitra (2009) analyzes a two-echelon inventory system with returns under generalized conditions, and developed a deterministic and a stochastic model for the system.

There are other papers in the literature that present exact and approximate methods for a two-level inventory system consisting of one warehouse and multiple retailers under a continuous review (R, Q) policy. Forsberg (1996) evaluated holding and shortage costs for a two-level inventory system with one warehouse and different retailers. Axsäter (1998) presents methods for the exact evaluation of two retailers' cases and an approximate evaluation for the case of more than two retailers.

Moinzadeh (2002) considers a single product supply chain consisting of one supplier and multiple identical retailers. He proposed a supplier replenishment policy that incorporates information about the inventory position at each of the retailers and provides an exact analysis of the operating measures for such systems. Based on the numerical study, parameter settings are identified under which information sharing is most beneficial. Gürbüz et al (2007) present coordinated replenishment in a distribution system with multiple retailers, a single outside supplier, and one warehouse that holds no inventory. They considered both inventory and transportation costs in a supply chain under stochastic demand and proposed a new policy – the hybrid policy – which combines a traditional echelon policy with a special type of can-order policy. They analyzed three coordinated replenishment policies (installation-based, echelon-based and time-based) and compared their performance. The numerical results suggest that the hybrid policy provides significant improvement over other replenishment policies.

2.3 Literature Review on Metaheuristic Techniques for Multi-Echelon Supply Chain Problems

Industrial decision makers face complex problems, including large numbers of integer or binary variables, non-linearities, stochasticity, non-standard underlying utility functions, and logical or non-standard constraints and feasibility conditions (Jones et al., 2002). Researchers have proposed a variety of heuristic algorithms to address them. Heuristic algorithms are solution methods that do not guarantee an optimal solution, but in general can generate a near-optimal solution relatively quickly. In recent years, metaheuristic algorithms such as Ant Colony Optimization (ACO), Evolutionary Computation (EC), Simulated Annealing (SA), Tabu Search (TS), Stochastic Partitioning Methods (SPM), and others, are widely used to solve important logistic and combinatorial optimization problems that include in their mathematical formulation uncertain, stochastic and dynamic information (Bianchi et al., 2006). They have been successful alternatives to the classical approach. According to Osman and Laporte (1996), the term metaheuristic describes an iterative search process that guides a subordinate heuristic by intelligently combining different concepts for exploring and exploiting the search space. The searcher employs learning strategies to structure information and find near-optimal solutions efficiently.

The major problems in supply chain belong to the category of NP-hard problems and they are computationally difficult (Jaramillo et al., 2002). As a result, much research effort has been devoted to develop an efficient solution methodology to find the optimal or near-optimal solution in the minimum computational time. Over the last few years, metaheuristic algorithms were successfully applied to large-scale and real-life network design problems: tabu search (see (Lee & Dong, 2009), (Tuzun & Burke, 1999)), genetic algorithms (see (Ko & Evans, 2007), (Min et al., 2006)), simulated annealing (see (Jayaraman et al., 2003)). Tuzun and Burke (1999) introduce a two-phase tabu search approach. The first phase searches for a good facility configuration, and the second phase searches for a good routing that corresponds to that configuration. Wu et al. (2002) proposed a decomposition-based heuristic method for solving the location-routing problem with capacitated depots. They used simulating annealing algorithm to solve decisions variables.

Evolutionary algorithms are a particularly important subset of population-based metaheuristic search approaches. Among these methods, Genetic Algorithm (GA) is a solution method that was formally introduced in the United States in the 1970s by John Holland at University of Michigan. GA is an intelligent optimization technique that has the capacity to solve difficult problems in a variety of disciplines. Its simplicity permits us to use GA to solve NP-hard problems in acceptable computational time.

GA has been applied to numerous supply chain management problems in many different configurations (Zhao & Xie, 2002). New algorithms based on the GAs have been developed for the set-covering problem ((Al-Sultan et al., 1996); (Beasley & Chu, 1996)), and for location-allocation problems ((Jaramillo et al., 2002); (Zhou et al., 2002)). Zhou and Liu (2003) proposed a capacitated location-allocation problem with stochastic demands. For solving these stochastic models efficiently, the network simplex algorithm, stochastic simulation and genetic algorithm are integrated to produce a hybrid intelligent algorithm. Lin et al. (2007) compared flexible supply chains and traditional supply chains with a hybrid genetic algorithm. Liao and Hsieh (2009) optimized the location decision for distribution centers with two objectives: minimization of total cost and maximization of customer service by using NSGA II algorithm.

GAs has also been successfully used to find the optimal solutions for inventory optimization. Sarker and Newton (2002) investigate the use of genetic GAs for solving the batch size problem for a product, and purchasing policy of associated raw materials. In the mathematical model for this problem, they considered a constrained nonlinear integer program. Abdelmaguid et. al. (2006) have offered a fresh Genetic Algorithm (GA) approach for the Integrated Inventory Distribution Problem (IIDP). They have developed a genetic representation and utilized a randomized version of a previously developed construction heuristic in order to produce the initial random population. Their experimental results showed the significance of the GA approach. On average, GA outperforms the previously construction algorithm and generates solutions that are within 20% of the optimal solution.

A genetic algorithm which has been adopted to cope with the production-inventory problem with backlog in the real situations was presented by Lo (2008)**.** Lo offered a model that considers a dynamic production-inventory environment. Besides optimizing the number of production cycles to generate a (R, Q) inventory policy, an aggregate production plan can also minimize the total inventory cost on the basis of reproduction interval in a given time horizon. Daniel and Rajendran (2006) addressed the problem of determining base stock levels to be held at the different stages in a serial supply chain under a controlled periodic review inventory system. A GA is proposed to determine the best base-stock levels. They also considered different supply chain settings (deterministic and stochastic lead time) to simulate and analyze the performance of the supply chain; their result showed the proposed GA algorithm is not significantly different from the optimal solution.

Radhakrishnan et. al. (2009) develop a novel and efficient approach using genetic algorithm to solve the complex inventory problem of the situation of multiple products and multiple members of the supply chain. They obtained the optimized stock levels for each member of the supply chain. Their approach to inventory management has minimized the total supply chain cost and determined the products that caused the supplier to incur additional holding cost or shortage cost.

Particle swarm optimization (PSO) is a stochastic optimization technique based on population inspired by social behavior (Kennedy & Eberhart, 1995). Bachlaus et al

(2008) explored the integration of production, distribution and logistics activities at the strategic decision making level where the objective is to design a multi-echelon supply chain network considering agility as a key design criterion. They formulated the problem mathematically as a multi-objective optimization model that aims to minimize the cost (fixed and variable) and maximizes the plant flexibility and volume flexibility. In order to solve the underlying problem, they proposed a novel algorithm entitled hybrid taguchi-particle swarm optimization (HTPSO). Huang et al (2008) designed a supply chain network in uncertain environment, in which the demands of the customer are taken as random variables and the operation costs involved are programmed using fuzzy neural network and optimized by particle swarm optimization to solve the established model. Silva and Choelho (2007) developed an optimization model of a simplified supply chain, including stocks, production, transportation and distribution, in an integrated production-inventory-distribution system, introducing PSO in supply chain issues.

Chapter 3

Metaheuristic Techniques for Complex Optimization Problems

Many well-known optimization problems with industrial applications are intractable. They are known as NP-Hard problems. For NP-hard optimization problems, it is often impossible to apply exact algorithms to large instances in order to obtain optimal solutions in a reasonable amount of computation time. Thus, in the past few decades, many heuristic algorithms have been proposed to solve complex combinatorial problems. Heuristic algorithms are solution methods that do not guarantee an optimal solution, but in general can generate a near-optimal solution relatively quickly, compared to exact algorithms. An important subclass of heuristics is metaheuristic algorithms, which was first introduced by Glover (1977). One of the definitions for metaheuristic is given by Osman and Laporte (1996):

"*A metaheuristic is an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions*."

In this chapter, the basic concepts of some metaheuristics such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are introduced. A brief description of GA and PSO is provided in Section 3.1 and Section 3.2 respectively. Section 3.3 briefly highlights Pareto-based multiobjective metaheuristics algorithms to achieve trade-off between conflicting objectives.

3.1 Introduction to Genetic Algorithm

Since the 1960s metaheuristics that are based on artificial reasoning have been widely used to develop powerful algorithms for difficult optimization problems (Gen & Cheng, 2000). Evolutionary algorithms are an important subset of random-based solution space searching methods. These algorithms are derived from the process of evolution in biology. Among these methods, Genetic Algorithm (GA) is a metaheuristic search technique that belongs to the class of Evolutionary Algorithms inspired by principles from natural selection which had been formally introduced in the United States in the 1970s by John Holland at University of Michigan (Holland, 1975). Once the theoretical foundations of GAs were established, GAs became an intelligent optimization technique adopted to solve many difficult problems. The flowchart of a simple genetic algorithm is summarized in Figure 3-1.

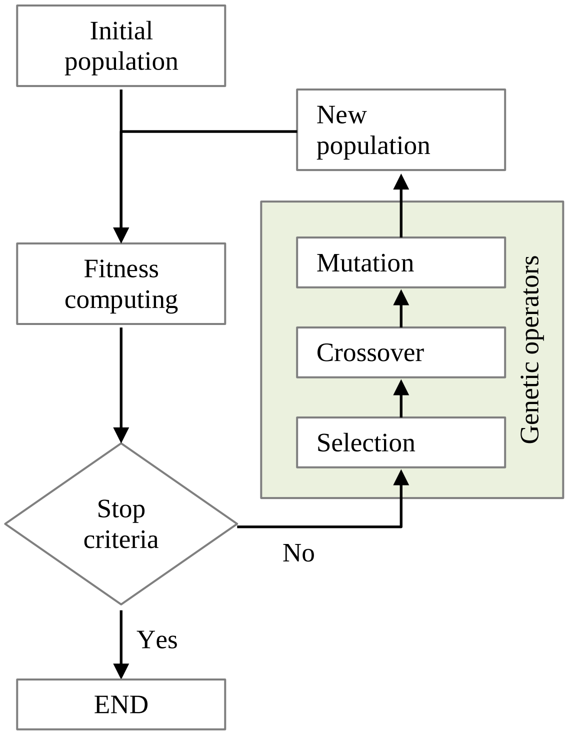


Figure 3-1: Flowchart of a simple Genetic Algorithm (adapted from (Gen & Cheng, 2000))

GAs operate in the same manner as biological evolution and the natural selection of organisms. In a simple genetic algorithm, the application starts with a set of solutions (initial population) created using some encoding method. Each candidate solution is represented as a chromosome or individual. The number of individuals in a population is called the *population size*. Traditionally, genetic algorithms have mostly used two common coding methods: binary representation and real number representation (Gen & Cheng, 2000). Once the initial population is generated, a fitness value is assigned using the objective function to each individual in order to obtain the quality of all individuals to survive and recombination. Then, the selection process is used to generate a mating pool. The highly fit individuals have a better chance of being selected. The recombination process starts by selecting parents from the mating pool and generating a new population using genetic operators: crossover and mutation. The new population is evaluated further. This process is repeated a number of times, and typically leads to better and better individuals. In summary, the concept of a genetic algorithm has six fundamental steps: representation of solutions to the problem, initialization of population, an evaluation function rating solutions in terms of their fitness, selection, genetic operators that alter the genetic compositions of children during reproduction, and termination criteria. The pseudo code of a simple genetic algorithm is as follows (Goldberg, 1989):

Algorithm 3-1: Basic genetic algorithm pseudo-code

```
begin
   for i = 1 to number of individuals do
        initialize values of individuals
   end
   Evaluate Population P()
   while generation < maxGenerations do
            Selection();
             Recombination ();
            Mutation ();
            Evaluate ();
            generation ++;
   end while
 end begin
```

3.1.1 Genetic Algorithm Operations

Selection

The selection mechanism is one of the main components in GA and is the first operator applied on a population to produce a new generation. In programming, memory is opened in reserve for the individuals selected to breed. This memory is called the mating pool (Yu & Gen, 2010). Like in natural selection, better individuals have higher probabilities of breeding. There exist a number of selection operators in GA literature. In this section, three basic selection mechanisms will be briefly described: roulette wheel selection, rank-based selection and tournament selection.

Roulette-wheel Selection: Roulette-wheel selection proposed by Holland is the one of most known selection methods among genetic algorithms (Gen & Cheng, 2000). The basic idea is to determine the selection probability or the relative fitness value for each chromosome proportional to the fitness value. This relative fitness value can be defined as follow:

$$p_i = \frac{f_i}{\sum_{i=1}^{popsize} f_i} \quad 3\text{-}1$$

In roulette wheel selection, the process is based on spinning the wheel a number of times equal to the population size by applying a random experiment, each time selecting an individual chosen by the roulette-wheel pointer. After obtaining a random number, whenever we find an individual that satisfies the random number between $\sum_i^k p_i$ and $\sum_i^{k+1} p_i$, the individual is selected into the mating pool (Yu & Gen, 2010).

Rank-Based Selection: Baker (1985) introduced ranking selection. The population is sorted from best to worst based on the objective function value in order to rank individuals. Rather than using absolute values, selection probabilities are computed based on rank values. Ranking might be needed under two conditions (Gen & Cheng, 2000). The first is that the exact fitness values cannot be determined. The second condition is that the population has an extremely fit individual. In that case, the extremely fit individual has a very high selection chance over all other individuals.

Tournament Selection: Tournament selection operates by selecting m individuals randomly from the population. The value m is called the tournament size. The individual with the highest fitness is termed the winner. The best one wins the tournament and is selected into the mating pool (Miller & Goldberg, 1995). Tournament selection process is repeated until the mating pool equals the size of the population. For m=2, the selection procedure is called binary tournament selection. The main characteristics of tournament selection make it quite useful in some situations, such as multiobjective optimization (Yu & Gen, 2010). These properties are defined as follow:

- Tournament selection only uses local information.
- Tournament selection is very easy to implement and its time complexity is small.
- Tournament selection can be easily implemented in a parallel environment.

Selection pressure is an important factor of a selection algorithm because it directly affects the average problem-solving quality of the population (Xie et al., 2007). In tournament selection, selection pressure is easily adjusted by using different tournament sizes; the larger the tournament size, the higher the selection pressure. At low selection pressure, the rate of convergence towards the optimum is likely to be slow (Legg et al., 2004). At high selection pressure, the genetic algorithm converges too fast and it typically results in obtaining local optima.

Recombination

Once individuals are selected, the next phase of genetic algorithm is the application of variation operators such as the crossover and mutation. Crossover is the main genetic operator of recombination process. The crossover operator combines (mates) two chromosomes (parents) to produce a new chromosome (offspring). A simple way to achieve crossover is one-point crossover (classical crossover) proposed by Holland (1975).

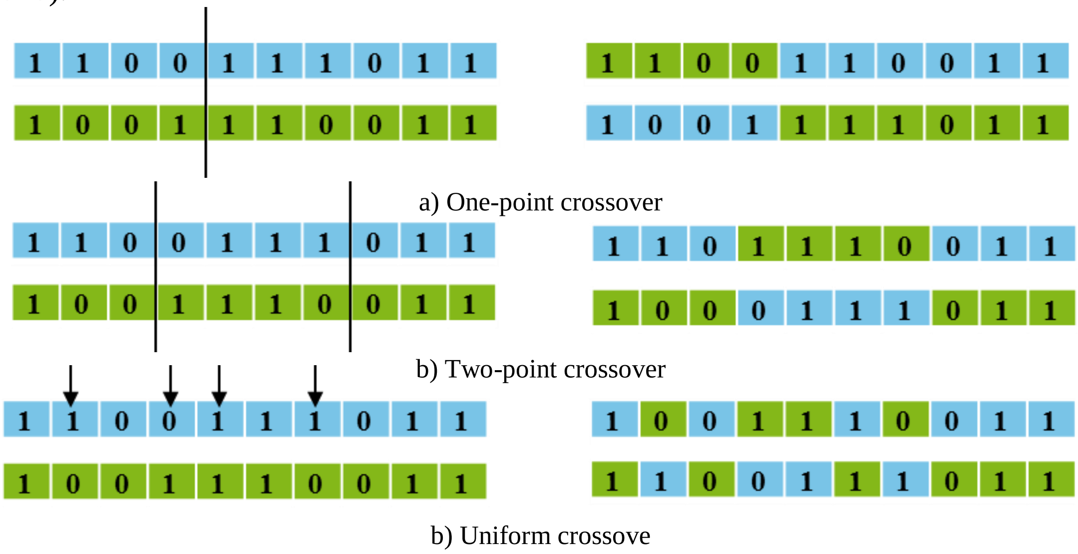


Figure 3-2: Crossover

The classical crossover operator takes two parents from a mating pool and chooses a random cut-point. It then generates offspring by interchanging two parent chromosomes at this point. In the literature, many different crossover types have been used such as two-point crossover, multi-point crossover and uniform crossover. In a two-point crossover two cut points are chosen randomly in parent chromosomes. The section between selected cut points is exchanged between two offspring. In most cases, the number of crossover points has been fixed at a very low constant value of 1 or 2 (William, 1995). However, there are situations in which having a higher number of crossover points is more useful for solving optimization problems. The crossover rate is defined as the ratio of the number of offspring produced in each generation to the population size. A higher crossover rate allows deeper exploration of the solution space and reduces the chances of settling for a false optimum, but it also results in wasting a lot of computation time exploring the unpromising regions of the solution space (Gen & Cheng, 2000).

The mutation operator is used to modify genes (decision variables) randomly in a selected chromosome with a certain probability in order to find new points in the search space. Mutation of each chromosome in the population occurs according to mutation rate which is chosen by the user. Therefore, it is not applied to every chromosome in the population. The choice of mutation rate critically affects the performance of GAs. Figure 3-3 shows the main two mutation operations: one-point mutation and uniform mutation. In binary coded chromosomes, genes can have a value of either 0 or 1. On the other hand, for real-encoded chromosomes, the mutation operator may be uniform mutation, boundary mutation, real number creep mutation, or dynamic mutation (Park, 2008).

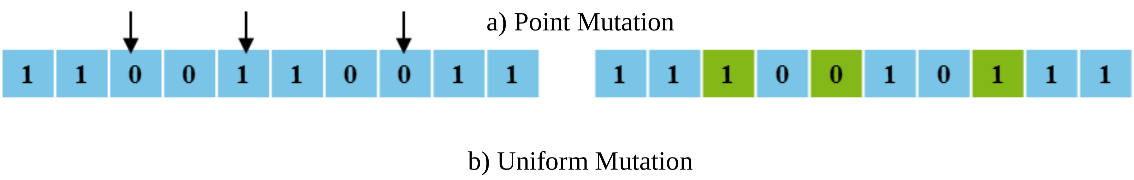
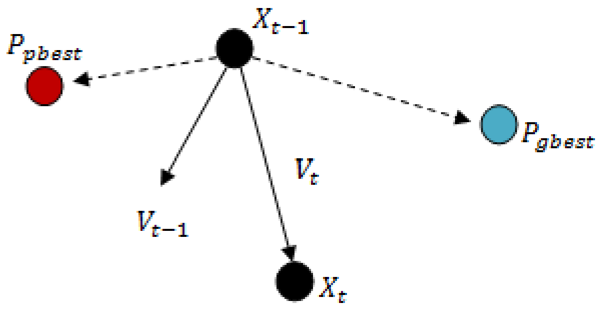


Figure 3-3: Mutation

3.2 Introduction to Particle Swarm Optimization

Swarm is generally used to describe social insects or social animals, e.g., ant colonies, bee colonies, fish schools, and bird flocks (Yu & Gen, 2010). Particle swarm optimization (PSO) is another stochastic population-based metaheuristic inspired by social behaviors of bird flocking or fish schooling (Kennedy & Eberhart, 1995). The main concept of PSO is very similar to other evolutionary computation techniques like GAs. However, it does not have genetic operators like mutation and crossover. The PSO algorithm consists of a swarm of particles, each represents a solution point in a multidimensional, real valued search space of possible solutions. These particles fly across the hyperspace based on the social psychological tendencies of individuals (Baghel, 2009). The position of each particle changes according to its own experience and the experience of neighboring particles.

In the PSO algorithm, each particle maintains its position in the search space with the velocity influenced by the best solution found so far by each particle (the personal best) and the best solution found so far by the whole swarm (the global best) (Shi & Eberhart, 1999). The last part of the velocity considered in the algorithm is inertia: the particle’s memory of its previous velocity. Once the particle’s velocity along a dimension is adjusted, a new position is computed based on Equation 3-3. Each particle in a swarm begins randomly in the domain space of the function to be optimized. Once the particles are initialized, a loop starts to find an optimum solution. In the loop, the particles’ velocity and positions are updated as described above. The algorithm is terminated with a predetermined stopping criterion.



X_{t-1}: current position, X_t : modified position, V_{t-1}: current velocity, V_t: modified velocity, P_{pbest}: local best position, P_{gbest}: global best position

Figure 3-4 Concept of modification of a searching point by PSO

The complete algorithm for the PSO is listed in Algorithm 3-2. Shi and Eberhart (1998) introduce, in the n-th dimension of the search space, more widely used formulae to calculate each particle's velocity (V^n) and position (X^n):

$$V_t^n = w \times V_{t-1}^n + C_1 \times rand_1 \times \left(P_{pbest}^n - X_{t-1}^n\right) + C_2 \times rand_2 \times \left(P_{gbest}^n - X_{t-1}^n\right) \tag{3-2}$$

$$X_t^n = X_{t-1}^n + V_t^n \tag{3-3}$$

where

n	number of elements in a particle,
w	inertia weight of the particle,
t	generation number,
C_1, C_2	acceleration constants,
$rand$	random value between 0 and 1
P_{pbest}^n	local best position of the particle,
P_{gbest}^n	global best position of particle in the swarm.

Algorithm 3-2: PSO algorithm pseudo-code

```
begin
   for i = 1 to Number of particles do
         initialize position and velocity randomly
         Evaluate Particle()
         Initialize Pbest()
   end
   while generation < maxGenerations do
            for each particle do
                  selectLeader()
                  updateVelocity()
                  updatePosition()
                  Evaluate()
```

```
            Update Pbest()
        end for
    Update Pgbest()
    generation ++
end while
end begin
```

3.2.1 Parameter Selection of PSO

The inertia weight w has an important role in the PSO algorithm. It is used to control the impact of the previous history of velocities on the current velocity. A large inertia weight factor encourages exploration of the entire search space while a lower value of inertia weight facilitates local exploration (Akbari & Ziarati, 2011). Therefore, the inertia weight proposed by Shi and Eberhard (1998) decrease linearly with the number of generations. This can be done using:

$$w = w_{max} - \frac{w_{max} - w_{min}}{t_{max}} \times t \tag{3-4}$$

where w_{max}, w_{min} is the maximum and minimum inertia weight, t is iteration number and t_{max} is the maximum iteration.

Particles' velocities on each dimension are clamped by V_{max}, the maximum allowable velocity for particles to keep particles from moving too far beyond the search space. If V_{max} is very low, a particle may not explore sufficiently, and if is too high, then particles may move beyond a good solution. In case the velocity of the particle exceeds V_{max}, then it is reduced to V_{max}. A maximum velocity V_{max} proposed by Abido (2007) is calculated with a user-specified velocity clamping factor k where the search space is bounded by $[X_{min}, X_{max}]$ in the following formula:

$$V_{max} = k \times \left(\frac{X_{max} - X_{min}}{N}\right) \tag{3-5}$$

where N is a selected number of intervals.

Parameters C_1 and C_2 control the movement of each particle towards its best position and the global best position, respectively. In other words, these two rates control the relative influence of the memory of the neighborhood and the memory of the particle. Recent work reports that choosing larger cognitive parameter, C_1, than social parameter, C_2, but with $C_1 + C_1 \leq 4$, produce a better performance (Ozcan & Mohan, 1998). In this dissertation, the acceleration constants C_1 and C_2 are chosen 2 as default values.

3.2.2 Quantum Particle Swarm Optimization for Combinatorial Problems

Since the original PSO algorithm can only optimize problems in which the elements of the solution are continuous real numbers, it is not possible to “throw to fly" particles in a discrete space (Kennedy & Eberhart, 1995). In recent years, several modifications of the PSO algorithm to solve discrete combinatorial optimization problems have been proposed in the literature ((Kennedy & Eberhart, 1997), (Al-kazemi & Mohan, 2002), (Yang et al., 2004)). Han and Kim (2002) developed the philosophy of Quantum-Inspired Evolutionary Algorithm for a class of combinatorial optimization problems. Based on the concept and principles of quantum computing, Quantum-Inspired Evolutionary Algorithm (QEA) uses Q-bit which is the smallest unit of information stored in a two state quantum system instead of using real numbers. In quantum computing, a Q-bit can be in “1” state, “0” state or in any superposition of state 0 and 1.

i) Representing a Q-bit Individual

The state of a Q-bit is defined as:

$$|\psi^i\rangle = \alpha|0\rangle + \beta|1\rangle \qquad \text{3-6}$$

where $|\alpha|$ and $|\beta|$ are complex number which denote the probability of the corresponding states, and $|\alpha|^2 + |\beta|^{\,2} = 1$. $|\alpha|^2$ gives the probability that the qubit is in the state of "0", $|\beta|^{\,2}$ gives the probability that the qubit is in the "1" state. A Q-bit individual as a string of n Q-bits can be represented as a Q-bit vector:

$$q = \begin{bmatrix} \alpha_1 & \alpha_2 & \alpha_n \\ \beta_1 & \beta_2 \cdots & \beta_n \end{bmatrix} \qquad \text{3-7}$$

Due to its capability to represent a linear superposition of states, Q-bit representation has better characteristic of population diversity during the search process of an evolutionary algorithm (Han & Kim, 2002). Like other evolutionary algorithms, QEA consists of the representation of individuals, evaluation functions as well as creating new generations. The first step of QEA is to initialize $Q(t)$ which represents a group of Q-bit individuals, $Q(t) = [q_1, q_2, \dots, q_m]$, where m is the population size, and q_j is the *j-th* Q-bit individual. The α and β for each qubit are initialized with $1/\sqrt{2}$ in order to ensure that the probability of observing the state "0" and "1" are equal. Once a population of quantum individuals is created, these can be used to evaluate the fitness of the objective function. The initial best solution is then selected among individuals and stored.

ii) Updating a Q-individual

In QEA, the state of a qubit can be updated by applying the operation with a quantum rotation gate U, which could be expressed as follows (Tayaran et al., 2011):

$$U(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \tag{3-8}$$

where Δθ is a rotation angle toward either 0 or 1 state and controls the speed of convergence. Each qubit from a quantum individual is updated as:

$$\begin{bmatrix} \alpha' \\ \beta' \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} \tag{3-9}$$

Table 4-1: Lookup table of the rotation angle (Tayaran et al., 2011)

x_i	b_i	$f(x) \geq f(b)$	$\Delta\theta$
0	0	$false$	0
0	0	$true$	0
0	1	$false$	$0.01\,\pi$
0	1	$true$	0
1	0	$false$	$-0.01\,\pi$
1	0	$true$	0
1	1	$false$	0
1	1	$true$	0

The idea in using the quantum rotation gate is to speed up the convergence by steering the direction of the individuals towards the better parts of the search space. Table 1 provides a convenient database for selecting the correct $\Delta\theta$, which is determined by the quantum chromosome, where x_i is the *i-th* bit of the current binary solution, b_i is the *i-th* bit of the current best solution.

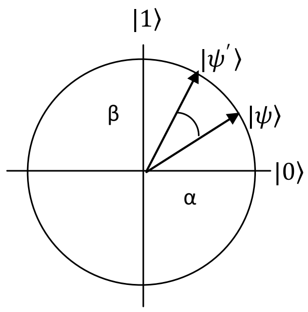


Figure 3-5: Polar plot of rotation gate for qubit individuals

3.3 Multi-Objective Optimization

In many real-world situations, decision-makers have encountered problems that are very complex and quite hard to solve using classical optimization techniques. It is easy to see that most practical optimization problem involve multiple and conflicting objectives that must be optimized simultaneously. For example, consider retailer stores stocked with inventories of material and replenished by a warehouse where one is trying to determine the optimal inventory control parameters. It is one of the most difficult planning decisions in all of logistics. Minimizing the overall cost will ultimately lead to reduced cycle stock at each stock point. But lower cycle stock leads to increase the number of cycles per year and correspondingly the number of times the company is exposed to the possibility for a stockout to occur. When only looking at one objective, the other objective suffers. However, in this case the goal may be to establish a policy that minimizes the level of their stocks without reducing availability. Thus, for such problems, multiple objectives need to be optimized together while satisfying the imposed constraints. A multiobjective optimization problem can be defined as follows (Gen & Cheng, 2000):

$$maximize\ /\ minimize\ \{z_1 = f_1(x), z_2 = f_2(x), \dots, z_m = f_m(x)\}$$

$$s.t. \quad g_i(x) \leq 0, \quad i = 1, \dots, q$$

$$h_j(x) = 0 \quad j = q+1, \dots, k$$

where x is called the decision vector, f_i is objective i, g_i is inequality constraint and h_j is equality constraint j.

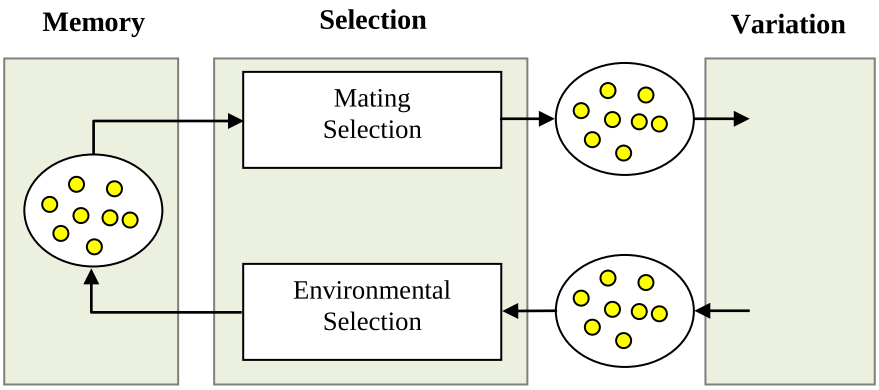


Figure 3-6 Components of a general stochastic search algorithm (Zitzler et al., 2004)

Several solution methods have been used to solve multiobjective optimization problems in the literature. A general stochastic search algorithm consists of three parts: i) a working memory that contains the currently considered solution candidates, ii) a selection module, and iii) a variation module as shown in Figure 3-6 (Zitzler et al., 2004). There is usually a set of solutions for the multiple objective cases that cannot simply be compared to one another. Such kinds of solutions are called non-dominated solutions or Pareto optimal solutions, for which no improvement in any objective function is possible without sacrificing at least one of the other objective functions (Gen & Cheng, 2000).

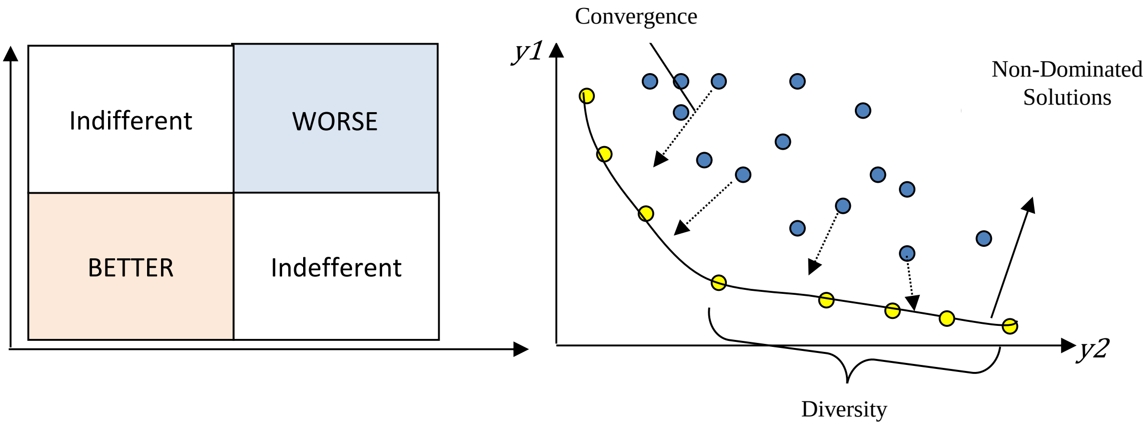


Figure 3-7: The Pareto front of a set of solutions in a two objective space (adapted from (Sastry, 2007))

The non-dominated solutions are defined as solutions that dominate others but do not dominate themselves. A Solution X in objective space is said to be a Pareto-optimal (non-dominated solution), if and only if there is no other solution Y in the search space that could dominate X. In other words, X dominates Y if X is better than Y in at least one objective function and not worse with respect to all other objective functions (Yu & Gen, 2010). The set including all Pareto-optimal solutions is termed the Pareto set and represents the optimal trade-offs between objectives. Figure 3-7 illustrates these concepts for a two-objective minimization problem, where it is desirable to have small values for each objective.

3.3.1 Multi-Objective Optimization with Genetic Algorithm

Over the last two decades, many efficient multiobjective evolutionary algorithms that are possible to find Pareto optimal solutions have been proposed based on non-dominated sorting suggested by Goldberg (1989). Among the most widespread methods, the algorithms maybe classified as follow: VEGA (Vector Evaluated Genetic Algorithm) (Schaffer, 1985), MOGA (Multi Objective Genetic Algorithm) (Fonseca & Fleming, 1993), NSGA (Non-dominated Sorting in Genetic Algorithm) (Srinavas & Deb, 1994) and SPEA (Strength Pareto Evolutionary Algorithm) (Zitzler & Thiele,

1999) .

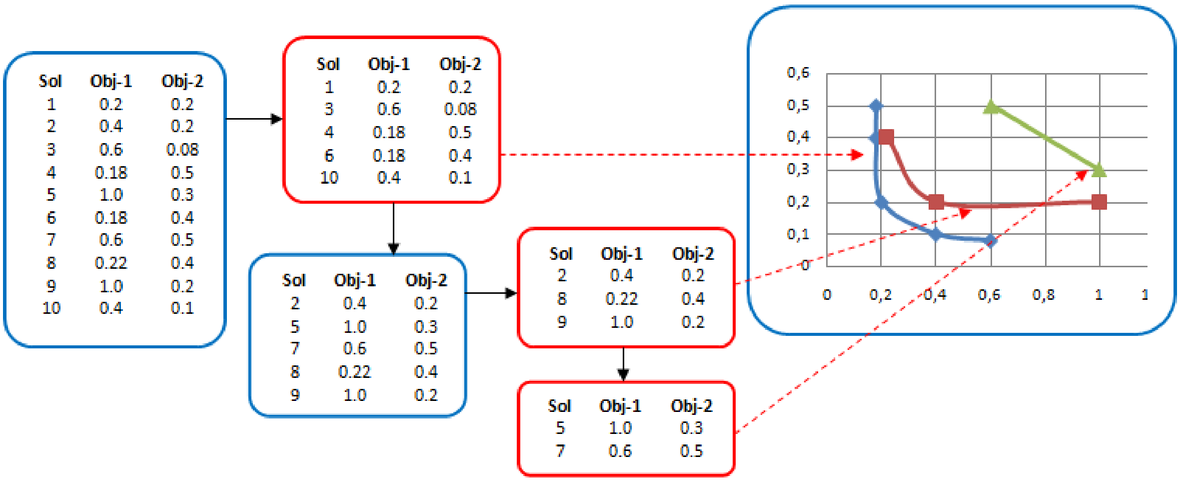


Figure 3-8: An example of the NSGA-II non-dominated sorting procedure (Sastry, 2007)

The Non-dominated Sorting Genetic Algorithm (NSGA) is one of the first MOGAs using Pareto ranking-based fitness assignment. While retaining the same concept of genetic operations, the main goals in MOGAs are mating selection and elitism. Individuals in the current generation are sorted into fronts with a non-dominated sorting procedure to decide on their chances for survival in the next generation. Each front of Pareto solutions is called a rank. The procedure begins by evaluating each solution in the current population. First, the set of solutions that are not dominated by any other solution in the current population are assigned rank 1. The non-dominated solutions among the unassigned solutions are assigned rank 2. That is, all solutions with rank 2 are dominated by at least one solution with rank 1, but are not dominated by others in the population. The above sorting and ranking procedure continues recursively until all fronts are identified. Figure 3-8 presents an example of the non-dominated sorting of population of ten solutions into three fronts (Sastry, 2007).

NSGA-II algorithm developed by Deb et al. (2002) has proved to be quite efficient in many different applications. They used an improved multiobjective non-dominated sorting method that requires a significantly smaller number of comparisons. In their method, a non-dominated sorting concept is used for each solution and it ranks all solutions to form non-dominated fronts as describe above. Therefore, with respect to Pareto optimality, solutions with lower ranks should be given priority for the selection process in the genetic operator. NSGA-II involves an initial random population P of size N. Genetic operators (binary tournament selection, crossover and mutation) are used to create an offspring population Q of size N. It then combines the parent population and the newly generated offspring population to create a combined population of size 2N. The combined population (P+Q) is sorted according to non-domination. Next, solutions from better non-dominated sets are chosen until N solutions have been chosen for the new population. To choose a new population with exactly N individuals, the solutions of the last front are sorted by using the crowded-comparison operator in descending order and choosing the best solutions needed to fill all population slots (see Figure 3-9). The resulting population is used for genetic operators to create the child population.

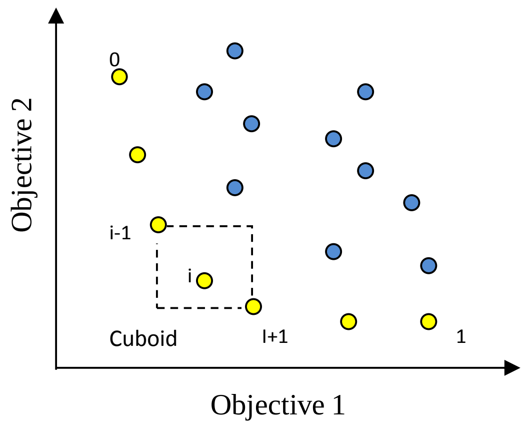


Figure 3-9: Crowding distance calculation (Raquel & Naval, 2005)

Apart from finding solutions in the Pareto front, it is essential to maximize the diversity of the achieved Pareto set approximation (Zitzler et al., 2004). While most recent multiobjective GAs (MOGA) use a niching mechanism to maintain the diversity among solutions in the objective space, the crowding distance technique, which is an estimate of the size of the largest cuboids enclosing that point without including any other point in the population, is applied in NSGA-II. It is calculated by taking the average distance of the two points on either side of the point in question along each of the objectives (Deb et al., 2002). The complete algorithm for NSGA-II is as follow:

Algorithm 3-3: NSGA-II pseudo-code

```
begin
  for i = 1 to Number of individuals do
        initialize values of individuals
  end
  while generation < maxGenerations do
     Evaluate Population P(t)
     Generate child population
            Tournament Selection()
            Recombination()
            Mutation()
```

Combine parent and offspring population R(t)=P(t)∪Q(t);
Sort R(t) based on Pareto dominance
Obtain non-dominated Fronts $F = \{F_1, F_2, \dots, F_n\}$
i←1
while $|P(t+1)| + |F_i| \leq N$ **do**
P(t+1) ← P(t+1) ∪ F_i
i ← i+1
end while
Sorting F_i based on crowding distance
j←1
while $|P(t+1)| < N$ **do**
P(t+1) ← P(t+1) ∪ s_j, where $s_j \epsilon F_i$
j ← j+1
end while
generation ++
end while
end begin

At each generation, NSGA-II employs crowded tournament selection operator which is a selection mechanism based on tournament selection. It randomly chooses a set of solutions from the mating pool. The tournament size generally equals two but it can be increased in order to obtain a better selection pressure (Xie et al., 2007). A comparison operator is used to compare the quality of two solutions based on their ranks. If the solutions are on the same non-dominated front or have the same rank, the selection is done based on their crowding distance, which is a measure of density of solutions in the neighborhood. (Deb et al. 2002).

3.3.2 Multi-Objective Optimization with Swarm Intelligence

Several multiobjective PSO techniques have been developed in the literature. One of the successful applications of PSO in multiobjective problems was proposed by (Sierra & Coello Coello, 2005). To apply a PSO algorithm in multiobjective optimization, the three main issues to be considered are (Sierra & Coello Coello, 2006):

- How to select particles to be used as leaders
- How to retain the non-dominated solutions found during the search process in order to report solutions
- How to maintain diversity in the swarm in order to avoid convergence to a single solution

Multiobjective Particle Swarm Optimization (MOPSO) proposes to use the Pareto dominance concept described in the previous section in order to handle multiobjective problems such as MOGA. The main challenge of MOPSO is to select the best global particle for each particle of the swarm to update its position (Durillo et al., 2009). Compared with the original PSO, multiobjective PSO (MOPSO) uses a set of leaders usually stored separately from the swarm, which is called an external archive (leaders archive). The leaders archive includes the best non-dominated solutions found since the beginning of the optimization. These solutions are used to update the positions of particles in the swarm (Sierra & Coello Coello, 2006). In that case, the quality measure plays an important role in the selection of one leader from the archive. The most common approach to select a leader from the archive is the tournament selection in which every non-dominated solution is considered as a potential leader. The pseudo code of MOPSO is described as follows (Abido, 2010):

Algorithm 3-4: MOPSO pseudo-code

```
begin
   for i = 1 to Number of particles do
        initialize position and velocity randomly
   end
   Evaluate Particle Swarm()
   Initialize Leaders External Archive()
   Compute Crowding Distance Values()
   Sort the non-dominated solutions according to crowding  distance()
   generation = 0
   while generation < maxGenerations do
             for each particle do
                  selectLeader()
                  updateVelocity()
                  updatePosition()
                  evaluation()
                  updatePbest()
             end for
        Update External Leaders Archive()
        Compute Crowding Distance Values()
        Sort archive according to the crowding distance()
        generation ++
   end while
   returnArchive()
end begin
```

Note that the external archive is limited in size in order to reduce computational time. The maximum size of the archive set is specified in advance. When the archive set is empty enough and a new non-dominated solution is detected, the new solution will enter the archive set. To decide which particles should remain in the archive when the maximum limit imposed on the size is reached, techniques such as the crowding distance concept are applied. The MOPSO steps can be defined as follow (Abido, 2010):

Step 1*: Initialize the population*. Set the generation = 0 and generate randomly n Particles.

Step 2: *Time Updating*. Update the iteration t = t+1.

Step 3: *Weight Updating*. Update the inertia weight (Equation 3-4)

Step 4: *Velocity Updating*. Compute the speed of each particle using the equation 3-2. If a particle violates the velocity limits, set its velocity equal to the proper limit.

Step 5: *Position Updating*. Compute the new positions of the particles adding the speed produced from the previous step according to the equation 3-3.

Step 6: *Non-Dominated Local Set Updating*. The criterion for deciding what position from memory to retain is Pareto dominance (i.e., if the current position is dominated by the position in memory, then the position in memory is kept, otherwise, the current position replaces the one in memory. If neither of them is dominated by the other, then we select one of them randomly)

Step 7: *External Set Updating*. This update consists of inserting all the currently non-dominated solutions into the leaders archive. The external particles are sorted into Pareto set and all dominated solutions are removed from the archive set. If the number of the individuals externally stored in the Pareto set exceeds the maximum size, the set is reduced according to the crowding distance concept.

Step 8: *Stop Criteria*. If the number of iterations exceeds the maximum, then stop. Otherwise, go to step 2.

Chapter 4

Integrated Strategic Network Design for Multi-level Supply Chains

Network design is a strategic decision that has a long-lasting impact on a company. To achieve an efficient supply chain, integrated distribution network design is essential. In this regard, suitable facility locations are a core part for a supply chain in the design of logistics systems (Li et al., 2011) (Blanchard, 2010). In general, optimally solving such an integrated network design problem in a reasonable computation time is a challenge, especially when inventory and routing are involved (Lei et al., 2003). In order to find out a good solution effectively, there is a need for new solution methodologies. The purpose of this chapter is to introduce an optimization model that explicitly captures the interdependency between different decision levels in supply chain (SC), while fulfilling the demand requirement, and to present computational results from extensive experiments that investigate the effects of several dynamic factors including stochastic demand and nonlinear cost functions. The network design problem is formulated as a multiobjective optimization problem taking into account the trade-off among transportation costs, facility location costs, inventory replenishment costs, and the service efficiency in terms of coverage distance. The service efficiency objective is to minimize the maximum distance between each covered customer and its closest opened DC to maximize demand satisfaction in a defined structure. The particular problem considered in this study contains a set of geographically dispersed retailers whose locations are known, and regional DCs located to help consolidate shipments and pool risk whose locations are unknown. Each retailer faces an independent distributed demand for a single product that must be met without shortage. This chapter begins with Section 4.1 presenting the formulation of integrated network design and logistic cost components. The next section introduces the notation and also provides a detailed formulation of the problem. Section 4.3 describes the solution methodology based on multiobjective metaheuristic techniques. A decision support tool to optimize the problem under consideration is developed and the case study is introduced in Section 4.4. Finally, the key results are summarized in Section 4.5 and 4.6.

4.1 Integrated Supply Chain Network Design

Integrated planning and control of a supply chain has three important dimensions (Shapiro, 2001). The first dimension is called as *functional integration* dealing with issues related to integration of purchasing, manufacturing and distribution activities within the company, between the company and its suppliers, and customers. The *geographical integration* refers to integration of these functions across various geographically distributed vendors, facilities and market. The third dimension is *inter-temporal integration*, which also is called hierarchical planning, involves coordinating decisions across strategic, tactical and operational levels of the supply chain. Distribution network design is one of the major strategic level issues that influence tactical and operational decisions due to the interdependence between these levels (Goetschalckx & Fleischmann, 2005). However, most literatures on network design have traditionally considered strategic, tactical, and operational decisions separately. This classical approach leads to considerable excess costs because the supply chain is optimized locally but does not guarantee the global optimum for the whole system. However, in global optimization, the objective is to coordinate all supply chain activities so as to maximize system performance by reducing cost, increasing service level, reducing the bullwhip effect, and using resources more effectively (Simchi-Levi et al., 2004). Moreover, to sustain competitive advantage in highly volatile market, inter-temporal integration is critical to the firm (Shapiro, 2001).

The integration and coordination of decisions at different planning horizons are quite difficult because it requires a complex trade-off analysis between various costs. For example, as the number of facilities in a supply chain increases, the inventory costs also increase due to increased safety stocks required to protect each distribution center against uncertainties in customer demands as shown in Figure 4-1 (Simchi-Levi et al., 2004) (Teo & Shu, 2004). Increasing the number of facilities increases the inbound transportation cost. On the other hand, the outbound transportation costs decrease because facilities are located closer to the market. Thus, if the number of facilities is increased to a point where there is a significant loss of economies of scale in inbound transportation, increasing the number of facilities increases total transportation cost (Chopra, 2003). Facility cost is decreased by reducing the number of facilities because of larger economies of scale. Moreover, it is often dependent on the capacity, as well as the location and demand characteristics (Teo & Shu, 2004). Consequently, integrating decisions affecting different planning horizons may lead to a better solution than non-integrated decisions.

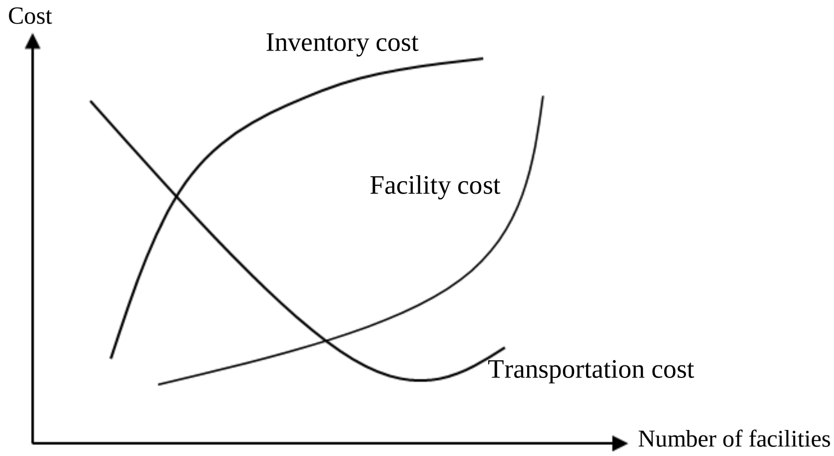


Figure 4-1: Relationship between number of facilities and logistics cost (Chopra, 2003)

Hence, the main components of distribution network design can be classified as: Facility location, Transportation, and Inventory (Perl & Sirisoponslip, 1988). As mentioned above, it is clear that these three key components are highly related; however, there has been limited available research on the integrated model. To illustrate the existing interactions between them and to achieve a better solution, these components should be jointly considered in the mathematical model. The first decision variable in the mathematical model includes the location issues that determine whether a facility should be located at a candidate facility site. The second decision contains the assignment variables that determine the allocation of zone demand to the open facilities. The last decision is how to manage the inventory at each open facility. Given a combination of these decisions, it is important to assign a set of performance indicators of the complete supply chain in order to identify the quality of the solution such as financial and logistics indicators (Ding et al., 2009). Financial indicators include all the costs related to network design such as investment costs, transportation costs and inventory costs. Logistics indicators include average demand fill-rate, average demand cycle time, probability of on-time delivery, etc.

As mentioned in Chapter 1, one of the purposes of this dissertation is related to the strategic network design (SND) module. *Strategic Network Design* module (SND) and the flow of information between different levels are shown in Figure 4-2. SND employ decision support through metaheuristic algorithms (e.g., genetic algorithms, particle swarm, etc.) to provide (near) optimal solutions to the supply chain design problem jointly considering various operating constraints of each supply chain process. At the demand planning level, sales forecasts are calculated based on historical data. The forecasted demand from *Demand Planning* is imported into the *Multisite Master Planning* where the available capacity and inventory costs are calculated based on average inventory levels (Meyr et al., 2005).

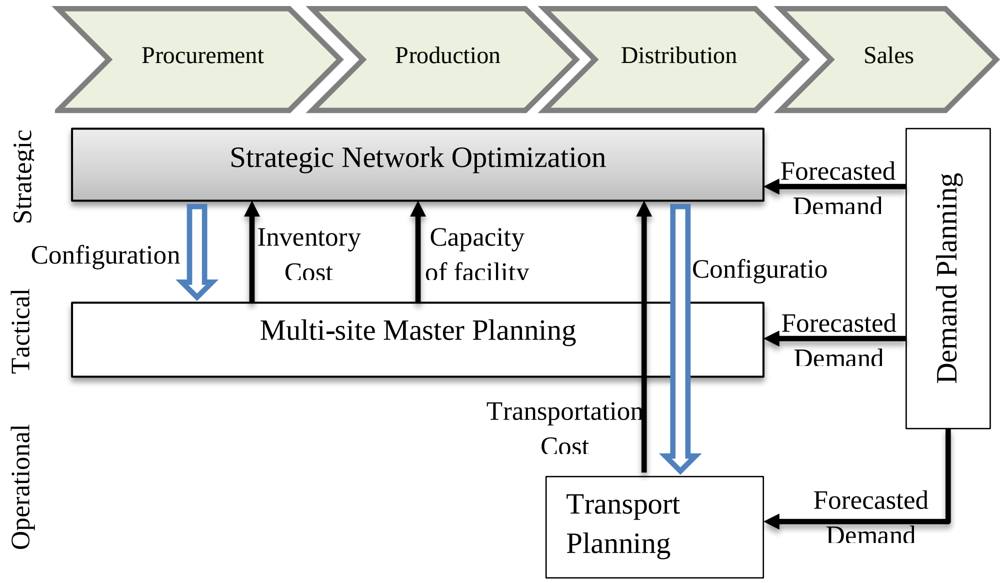


Figure 4-2: Coordination and information flows between decision levels for strategic network design tool (adapted from (Meyr et al., 2005))

At the *Transportation Planning* level, a mathematical expression is used to predict the average travel distance according to a given network configuration. The planned capacity, average inventory costs, and estimated travel distance are given to the SND to determine the optimal network configuration. The outcome of the SND module is given to the optimization tool to improve the current network configuration. Next, each part of the costs related to network design is explained in detail.

4.2 Model Notations and Problem Formulation

In this section, an analytical model for the integrated distribution network design problem is introduced. The problem is formulated as a multiobjective mixed-integer non-linear programming model so as to explore the tradeoff between conflicting objectives. Total annual cost is the sum of the cost to open DCs, the inventory cost (including ordering, holding and backorder costs) at the open DCs, and inbound and outbound transportation costs. It is assumed that the customers are uniformly scattered in a connected region, *A*. Each customer $i \in M = \{1,..., M\}$ has an independent distributed demand according to normal distribution. In order to represent the DC locations, a binary decision variable X_k is defined, which takes the value of 1 if the DC *k* is opened and 0 otherwise. In addition, to determine assignment of the retailer to DCs, another binary decision variable Y_{ik} is used, which takes the value of 1 if the retailer *i* is assigned to DC *k* and 0 otherwise. The following notation is used for the mathematical model:

Variables	**Definition**
index	
i	index for customers $(i = 1... M)$
k	index for candidate DCs $(k = 1...K)$
parameters	
D_k	average annual demand of point *k*
A	size of the service region (in square km)
μ_i	average daily demand at customer *i*
σ_i	standard deviation of daily demand at customer *i*
σ_k	standard deviation of daily demand at DC *k*
f_{kn}	fixed investment cost of locating a DC *k* at breakpoint *n*
c_{kn}	variable operating cost of DC *k* at breakpoint *n*
V_k	amount of the space requirement of DC *k*
d_{ik}	distance between DC *k* to customer i, for each $i \epsilon I$ and $k \epsilon K$
α	desired percentage of retailers orders satisfied (fill rate)
z_α	standard normal deviate such that $P(z \leq z_\alpha) = \alpha$
h	inventory holding cost per unit per day (€/unit-day)
ν	variable delivery cost per km from DC to customers (€/km)
F_k	fixed cost of placing an order at DC *k* (€/order)
c_{fk}	fixed shipment cost from external supplier to DC *k* (€/truck)
c_{vk}	variable inbound shipment cost per unit from external supplier to DC *k*
Q_k	order quantity at DC *k*
R_k	reorder point at DC *k*
L	lead time in days
W_{cap}	vehicle capacity
χ	planning horizon (days in a year)

4.2.1 Analysis of Facility Location Cost

Facility location costs for DCs or warehouses include three main components: handling costs, fixed costs for opening a new facility, and storage costs (Simchi-Levi et al., 2004). Handling costs include labor and utility costs, which involve the loading, moving, and unloading of materials. Handling costs due to the transit of products through the facility is often a direct function of the volume moved and depends on the characteristics of the product's family (Battini, 2008). Storage costs represent inventory carrying costs that are proportional to the level of inventories held. Fixed costs include all cost components that are not proportional to the amount of material that flows through the warehouse, but proportional to warehouse size (capacity) (Figure 4.3).

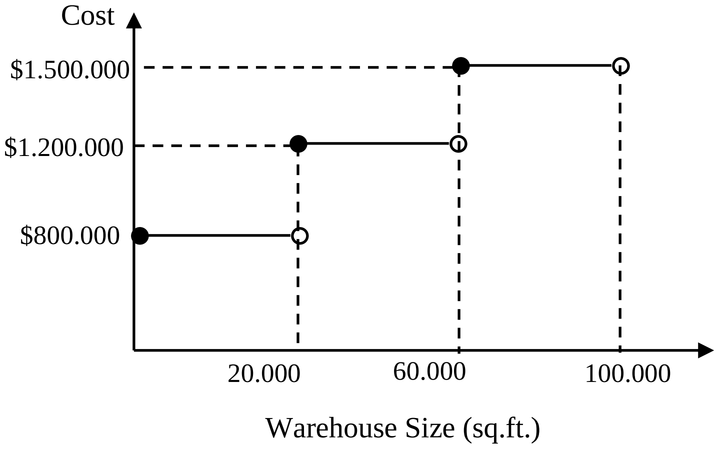


Figure 4-3: Fixed costs as a function of the warehouse capacity (Simchi-Levi et al., 2004)

Most of the research in the areas of facility location has focus on the linear transportation costs and one fixed location cost for each possible facility (Holmberg, 1994). However, the cost structure of a facility in the real-world problem can be more sophisticated than just considering fixed setup cost. To better suit real life situations, the facility location problem with staircase cost structure has been proposed by Holmberg (1994). This allows several fixed costs at different capacity levels, and also allows the linear operating cost coefficients to vary between different intervals of capacity amount. In this study, the cost open to DCs is categorized as a fixed investment cost that is in the unit of Euro (€) per year as well as a variable cost that is in Euro (€) per unit. Fixed investment cost is based on the DC's space requirement, server number, inventory size, or machine capacity, which should be determined by the storage area in square meters (Huang et al., 2009). Variable operating cost is calculated based on the product volume passing through the DC in a year and represents economies-of-scale in capacity acquisition to be built-in at each new facility (Verter & Dincer, 1995). Thus, total facility cost is a function of assigned customer demand. Goh et al. (2001) consider the warehouse sizing problem in the case where the model includes not only warehouse construction cost, but also inventory holding and replenishment cost. Similarly, to model the facility cost, it is assumed that only discrete choices of facility sizes are available, i.e., $s_0 < s_1 < \cdots < s_{n-1} < s_n$ are the possible DC sizes as shown in Figure 4-4.

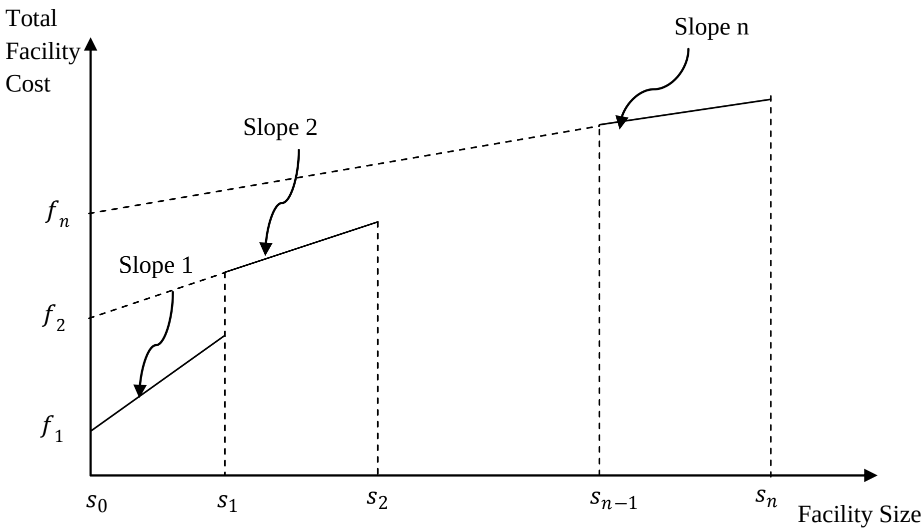


Figure 4-4: Operating Cost $F(V_k)$ of potential facility *k* versus facility size

The DC size is measured as the total number of storage spaces. The main problem is how to estimate the required space based on the annual flow of product through a DC. Since every pallet requires an empty space in the distribution center as well as space for aisles, picking, sorting, processing facilities and AGVs, the required storage space is typically multiplied by a factor (Simchi-Levi et al., 2004). A typical factor used in practice is three (Bramel & Simchi-Levi, 1997). According to Rosenblatt (1988), the nominal capacity requirement is given by:

$$V_k = \left(R_k + \frac{Q_k}{2}\right) \times d \qquad \text{4-1}$$

where d is average capacity required per unit stored. Let us denote the cost of allocating V_k units of capacity at facility k by $\mathrm{F}(V_k)$. The total facility cost of DCs can be formulated as follow:

$$C_O = \sum_{k=1}^{K} F(V_k) = \sum_{k=1}^{K} f_{kn} + c_{kn}D_k, \qquad s_{n-1} < V_k < s_n \qquad \text{4-2}$$

where f_{kn} is the fixed charge cost for opening a DC k at capacity s_n and c_{kn} is the corresponding variable operating cost per unit item for the capacity s_n.

4.2.2 Analysis of Transportation Costs

Transportation refers to the efficiency of moving products from raw material to finished goods between different facilities in a supply chain (Ma, 2003). Transportation cost is directly related to the type of product, size of shipment, and movement distance.

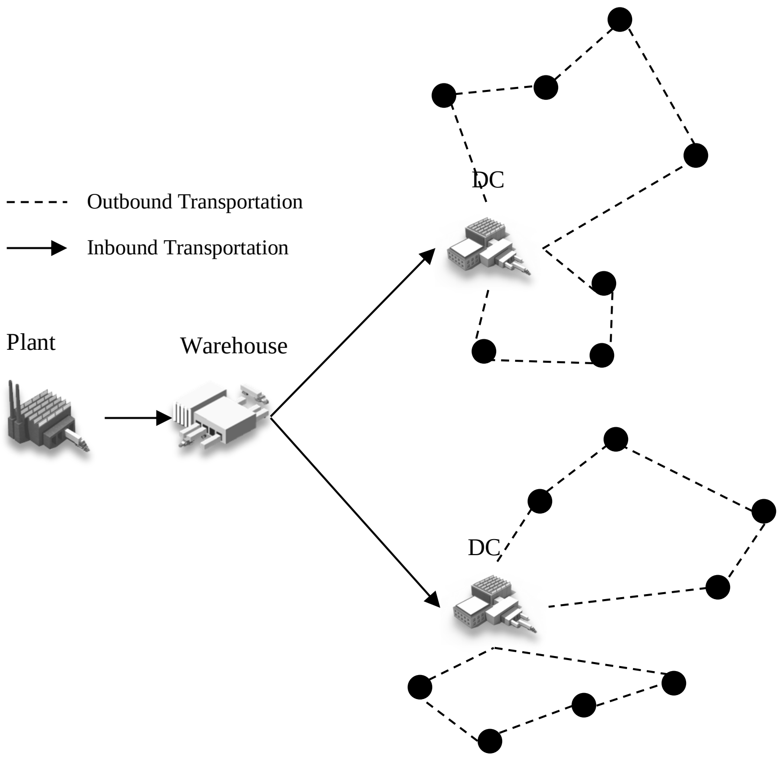


Figure 4-5: Inbound and Outbound Transportation of DCs

In general, logistic activities are divided in two major groups as inbound and outbound logistics. Inbound logistics is defined as the process of receiving goods from the upstream suppliers of a supply chain member, while outbound logistics are the activities between the supply chain member and its downstream customers (Harrison & Van Hoek, 2005). In the light of this definition, total transportation cost for a member of a supply chain can be categorized as inbound and outbound transportation costs (Mangotra et al., 2009). Taking the regional DC as the point of reference, inbound transportation costs are costs associated with the movement of products from the warehouse to the regional DC. The cost of shipping products to the retailers located within a DC's service area is referred to as the outbound transportation cost as shown in Figure 4-5. Both inbound and outbound transportation costs play one of the most significant roles in the establishment of the DC to a particular location.

Inbound Transportation Cost

The inbound transportation costs are classified into two categories (Bowersox et al., 2002). The first category comprises fixed costs, which are not directly influenced by the shipment volume. Fixed costs include vehicles, terminals, rights-of-way, information systems, and support equipment. The second category is variable transportation cost, which depends on volume, distance, and services provided, and it includes the direct carrier cost associated with the movement of each load. Variable transportation cost is generally measured as a cost per mile or per unit of weight. The inbound transport costs can be modeled as the one-origin/one-destination situation (Daganzo, 2005).

$$C_{IT} = \sum_{k=1}^{K} \left(c_{fk} + c_{vk} Q_k\right) \frac{D_k}{Q_k} \qquad \text{4-3}$$

c_{fk} is a fixed cost per shipment, c_{vk} is the rate at which the variable cost per shipment increases size. ($c_{fk} + c_{vk}Q_k$) express the inbound transportation cost incurred in a single shipment to a DC and D_k/Q_k is the expected number of inbound shipments to a DC during a year.

Outbound Transportation Cost

Outbound transportation refers to the movement of finished products to each retailer within the serving area of that particular DC. In many of distribution network design models, outbound transportation cost is simplified to the direct shipment (Shen & Qi, 2007), which refers to delivering freight directly from the origin to the destination without visiting any intermediate point. If each vehicle visits more than one customer, the problem is termed a Vehicle Routing Problem (VRP). VRP is a problem of finding the optimal routes of delivery for vehicles to minimize the total distance traveled, where a route is a tour that starts at the DC, visits a subset of the customers and ends at the DC. All customers must be visited exactly once by one vehicle and the sum of the demands of the visited customers on a route must not exceed the vehicle capacity.

A vehicle routing problem (VRP) is a well-known NP-hard (Non-deterministic Polynomial-time hard) problem and computational experience indicates that the VRP is difficult to solve to optimality within acceptable computation time. In the network design phase, it is only needed to estimate the total expected routing costs as a result of different facility locations instead of detailed route plan of vehicles (Shen & Qi, 2007). In this context, using continuous approximations, Daganzo ((1984), (2005)) proposed a simple closed mathematical expression to predict the travel distance in capacitated vehicle routing problems. In Daganzo’s approach, the optimal tour length is estimated by using the Euclidean distance between the center of the vehicle's routing zone and DC, the number of routes needed, the distance between consecutive stops within the service area, the number of points or nodes, and parameters that depend on the shape of the service area.

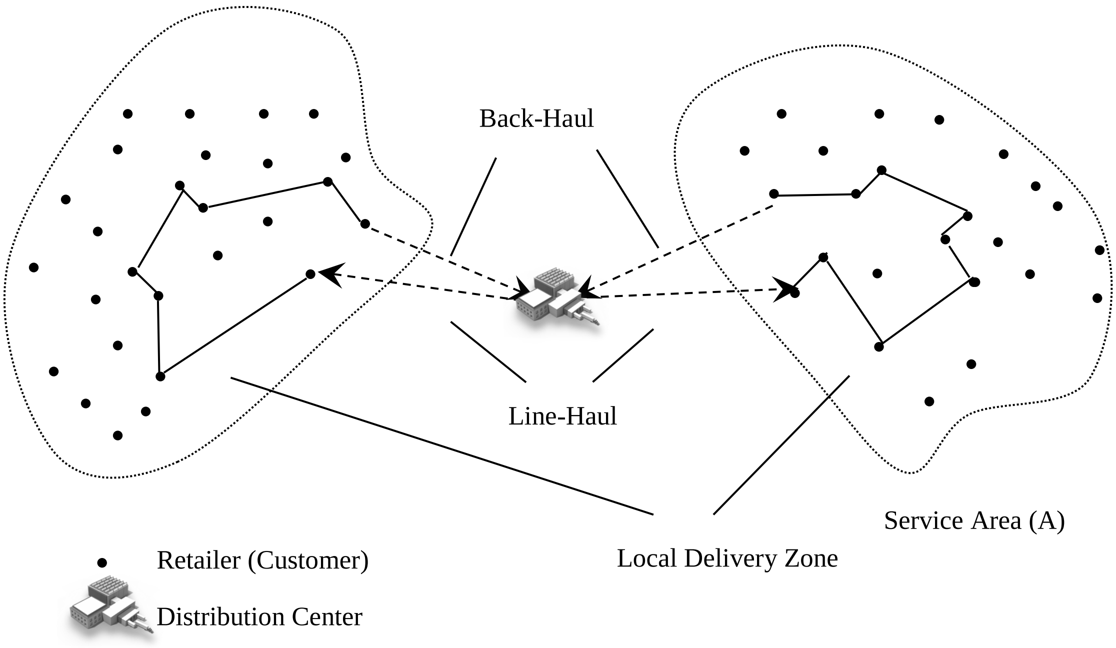


Figure 4-6: Approximation of average tour length

The continuous approximation technique (CA) has been applied to a variety of problems, e.g., the location-routing problem (Shen & Qi, 2007), production–distribution system design (Dasci & Verter, 2001), distribution-inventory planning (You et al., 2011), and delivery-route planning (Geunes et al., 2007). In the most basic case, for a given district of area *A* and *M* visiting points, the expected travelling salesman problem (TSP) distance travelled by a vehicle can be approximated as (Novaes et al., 2000) (Daganzo, 1984):

$$TSP \approx k_e\sqrt{MA} \tag{4-4}$$

where k_e is a proportionality constant equal to 0.75 when the Euclidean metric is considered. In this context, continuous approximation is used to estimate the length of routing between DCs and retailers without considering the detailed schedule. Daganzo (1984) proposes a simple and good approximation for the expected total tour length travelled by truck servicing *M* customers:

$$VRP_k \approx 2 \times \bar{l} \times \frac{M}{q} + TSP \tag{4-5}$$

In this expression, the average distance between the customers and the distribution center is $\bar{l}$, the maximum number of customers that can be served per truck is q.

Haimovich and Rinnooy Kan (1985) proposed the following formula to the upper bound of approximate the VRP tour distance:

$$VRP_k \approx 2\left\lceil\frac{M}{q}\right\rceil \bar{l} + \left(1 - \frac{1}{q}\right) TSP \qquad \text{4-6}$$

To address the expected tour length TSP, Shen and Qi (2007) divide A into two areas: A_1 that is occupied by the customers assigned to DC k, and A_2 that is occupied by the other $M - m$ customers. With this new definition, the length of the tour in local delivery zone is defined by Shen and Qi (2007) as follows:

$$TSP \cong k_e \sqrt{m} m \frac{A}{M} \sqrt{\frac{M}{mA}} = k_e m \sqrt{\frac{A}{M}} \qquad \text{4-7}$$

Thus the total delivery cost per year is calculated as follow:

$$VRP_j \approx \chi\, \nu \left(2 \frac{\left(\sum_{i=1}^{m} \mu_i d_{ij}\right)}{W_{cap}} + \left(1 - \frac{1}{W_{cap}}\right) k_e m \sqrt{\frac{A}{M}} \right) \qquad \text{4-8}$$

Shen and Qi (2007) test the performance of their approach using data sets from Christofides and Mingozzi (1979) and compare the solutions with those from a meta-heuristic (Agarwal et al., 2004) that produce optimal solutions. In the case of more than 50 customers, his computational results show the approximation error is bounded to 2% (Geunes et al., 2007).

4.2.3 Analysis of Inventory Cost

There are three fundamental questions that must be answered by a decision maker managing the inventory level at a location (Silver et al., 1998):

- How often should the inventory status be determined?
- When should a replenishment order be placed?
- How large should the replenishment order be?

In simplest terms, inventories can be categorized in five distinct forms: anticipation stock, cycle stock, safety stock, pipeline stock, and decoupling stock (Muckstadt & Sapra, 2010). A firm creates anticipation stocks not to meet immediate needs, but to meet requirements in the more distant future. Cycle stocks are necessary to meet current demand or to meet the average demand during the time between successive replenishments. Safety stock is the amount of inventory to protect against deviations from average demand during lead time. Safety stock should be considered in addition to the regular stock; its volume depends on lead time, demand variability, and service level. Pipeline stock refers to inventories in transit between echelons of the supply chain channel. Pipeline stock is equal to the expected demand over the lead time. Decoupling stock is defined as another type of safety stock used in manufacturing settings. In order to protect against variation in processing times or machine breakdowns at a station, inventories are introduced between successive stations. These inventories are called decoupling stocks. Shortage costs are paid when customer orders are not fulfilled or are set to be satisfied later when the product becomes available. They can be divided into two models: backorder or lost sales models (Ghiani et al., 2004).

- Lost sales costs: A lost sale is likely to occur if the unavailable items can be easily obtained from a competitor. Lost sales costs include the profit that would have made on the sale, and the negative effect that the shortage could have on future sales.
- Backorder costs: When goods are difficult to replace, a shortage often results in a delayed sale. Apart from the negative effect on future sales, a back order could result in a penalty.

For calculating the inventory holding cost at any located DC, a continuous review (R, Q) inventory policy is considered with service a level constraint that is a slight variation of the model proposed by Miranda and Garrido (2006). It means that a batch of size Q is ordered when the inventory position declines to R. If an order is submitted to the plant, the inventory level must cover the customers' demand during lead time with probability $1-\alpha$. The total mean demand assigned to a DC k is ($\sum_{i\epsilon m} D_i$) and D_i is ($\sum \chi\mu_i$), where *m* denotes the set of customers assigned to the DC. Since the customers' demands are assumed to be independent and normally distributed, the safety stock held at a DC is given by ($z_\alpha\sqrt{L}\sqrt{\sum_{i\in m}\sigma_i^2}$). The average total annual inventory cost including fixed order cost, holding cost, safety stock cost and inbound transportation cost can be formulated as follow:

$$F_k\frac{D_k}{Q_k}+\chi h\left(\frac{Q_k}{2}+z_\alpha\sqrt{L\sum_{i\in m}\sigma_i^2}\right)+(c_f+c_vQ_k)\frac{D_k}{Q_k} \qquad \text{4-9}$$

The first term in expression (1) is total fixed cost of placing orders per year. The second term is average holding cost and the average cost associated with the safety stock kept at DC k (\$/day). The third term is the expected inbound transportation cost at DC k. Minimizing the total costs, the optimal ordering quantity (Q_k^*) for DC k with differentiating the objective function in terms of Q_k can be expressed by Eq.4-11, based on the known EOQ model:

$$Q_k^* = \sqrt{\frac{2D_k(F_k + c_f)}{\chi h}} \qquad \text{4-10}$$

Replacing this expression into the objective function produces the following expression:

$$\sqrt{2\chi h\left(F_k + c_f\right)}\sqrt{D_k} + \chi h z_\alpha \sqrt{L}\sqrt{\sigma_k^2} + c_v D_k \qquad \text{4-11}$$

4.2.4 Integrated Supply Chain Network Design Function

The Set Covering Problem (SCP) is one of the most popular discrete optimization problems among facility location models (Chanta et al., 2011). In the SCP, one of the objectives is to find the location and optimum number of facilities. An important consideration in selecting the location of these facilities is the constraint that requires that all demands must be covered by at least one facility. As a special case of the more general SCP, the objective in this study is to find the best number and location of DCs that minimizes total logistics costs and maximizes demand satisfaction in a defined structure so that each customer is covered by at least one facility. The following are the decision variables for the mathematical model:

$$X_k = \begin{cases} 1, & if\ DC\ k\ is\ opened \\ 0, & \text{otherwise} \end{cases}$$

$$Y_{ik} = \begin{cases} 1, & if\ DC\ k\ is\ \text{assigned to customer i} \\ 0, & \text{otherwise} \end{cases}$$

The proposed analytical multiobjective mixed-integer non-linear programming model of integrated location-inventory can be formulated as:

Objective 1:
$$\min \quad TC = \sum_{k\epsilon K}\Bigg\{(f_{kn} + c_{kn}D_k)X_k + \theta\left[\frac{D_k}{Q_k}(g_k + a_kQ_k)\right] + \beta\left[F_k\frac{D_k}{Q_k} + \chi h\left(\frac{Q_k}{2} + z_\alpha\sqrt{L}\sqrt{\sigma_k^2}\right)\right] + \theta\chi\nu\left[2\frac{\left(\sum_{i=1}^{M}\mu_i d_{ik} Y_{ik}\right)}{W_{cap}} + \left(1 - \frac{1}{W_{cap}}\right)k_e\sum_{i=1}^{M} Y_{ik}\sqrt{\frac{A}{M}}\right]\Bigg\} \qquad \text{4-12}$$

Objective 2:
$$\min \quad CD = \{\max(d_{ij})Y_{ik}\} \qquad \text{4-13}$$

$s.t$
$$\sum_{k\in K} Y_{ik} = 1, \quad \text{for each } i \in I \qquad \text{4-14}$$

$$Y_{ik}\text{-}X_k \le 0, \quad \text{for each } k \in K \qquad \text{4-15}$$

$$D_k = \sum \chi\mu_i Y_{ik}, \quad \text{for each } i \in I \qquad \text{4-16}$$

$$\sigma_k^2 = \sum \sigma_i^2 Y_{ik}, \quad \text{for each } i \in I \qquad \text{4-17}$$

$$\sum_{i\in I}\mu_i Y_{ik} \le Cap_k X_k \quad \text{for each } k \in K \qquad \text{4-18}$$

$$X_k \in \{0,1\} \quad \text{for each } k \in K \qquad \text{4-19}$$

$$Y_{ik} \in \{0,1\} \quad \text{for each } k \in K \text{ and } i \in I \qquad \text{4-20}$$

The first term in the objective function (TC) (4-12) computes the fixed cost of locating facilities and the variable facility costs as a function of the facility size. The second term in the function computes the inventory costs with inbound transportation costs. The last term computes the transportation costs from the DCs to the customers. CD denotes the secondary objective that minimizes the maximum distance between each covered customer and its closest opened DC. β and θ are weight factors for inventory and transportation costs. Equation (4-14) ensures that each retailer is served by exactly one DC. Constraint (4-15) stipulates that the assignments can only be made to open DCs.

Expressions (4-16) and (4-17) compute the mean and variance of DC demand to mean (annual) and variance of customer demand (daily). Constraints (4-18) represent that the mean demand served does not exceed the DC's capacity. Finally, expressions (4-19) and (4-20) indicate that the design variables (X and Y) are binary.

4.3 Solution Methodology

As with the most combinatorial problems, exact methods are computationally feasible only for small/medium-sized problems (Pullan, 2009). For larger instances, it is therefore necessary to use faster heuristic methods. Thus metaheuristic algorithms are use in *Strategic Network Design* module (Figure 4-7). In this study, population-based metaheuristics for solving the multiobjective facility location-allocation problem such as PSO are proposed. Firstly, it presents the quantum particle swarm optimization algorithm (QPSO) that can be used to efficiently solve the combinatorial problem.

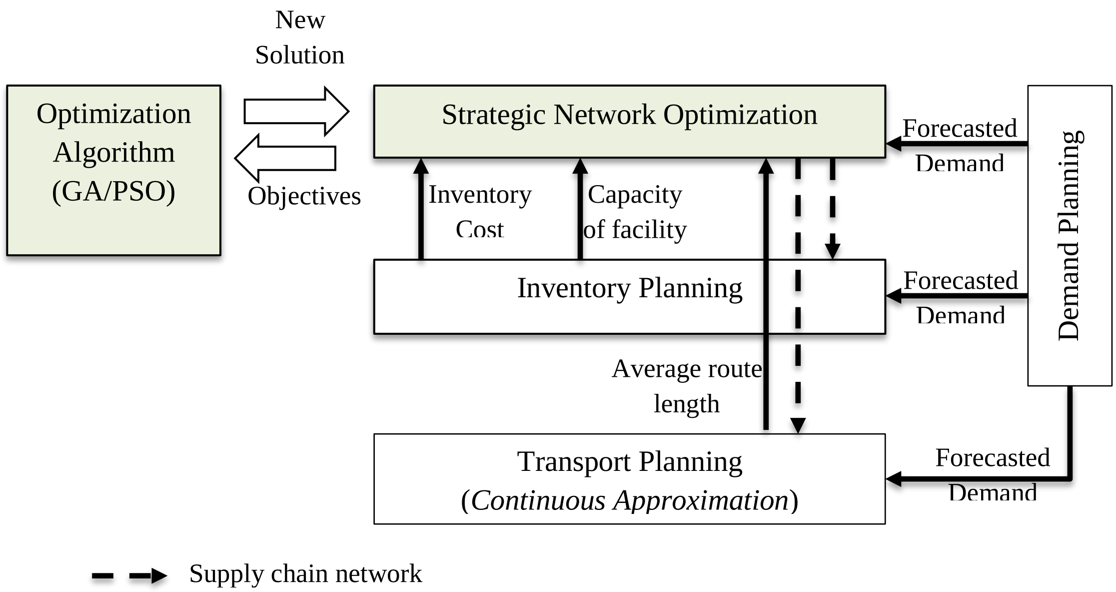


Figure 4-7: Strategic network optimization tool with metaheuristics

4.3.1 Application of Quantum-PSO for Location-Inventory Problem

The first step in a Quantum-PSO algorithm for a particular problem is to design individual particles representing the possible solutions and to avoid infeasible solutions in the population. The potential solution for the problem is encoded in a binary string with one position for every candidate location such that each binary encoding specifies the status of a candidate DC whether a given DC j is opened or closed (variables X_j). As "0" indicates that candidate site j is not to open, "1" in position j is interpreted to mean that candidate site j is selected to open. Each particle of QPSO described consists of binary values whose length is equal to the number of candidate DC nodes in the problem. For example the k^{th} particle of the population for an n-location problem could be given as,

$$I^k = \{1, 0\ , 0, 1, 0, 1, 0, 1, 1, 0\}$$

The above particle represents 10 candidate DCs such that DCs are identified by 1, 4, 6, 8, 9 have been selected to open on the ten possible locations. The steps of algorithm QPSO applied to solve the problem is given below:

Step 1: Initialize parameters. Load the parameters of M customers and K candidate DCs.

Step 2: Initialize particle swarm. Randomly generate a particle swarm based on single dimensional array, which consists of K binary values representing decision variables related to open or close the DC.

Step 3: Allocate customers to the open DC. A greedy heuristics used to assign customer to open DCs. This procedure assigns each customer to its nearest DCs. If it is not possible to assign a customer to its nearest DC because of excessive capacity, it is assigned to the second nearest DC with sufficient capacity, and so on.

Step 4: Compute the fitness value. After allocation process, fitness values of each particle in swarm are calculated by using Equation 4-11 and 4-12.

Step 5: Apply quantum particle swarm optimization steps described in previous section.

Step 6: Obtain the optimal solution and the total cost of integrated facility location-inventory problem.

In this research, local search was not used, which improves the solution with the k-change neighborhoods procedure. Daskin et al. (2005) introduced three main reasons for not considering the improvement of the cost by shifting assignments of customer to DCs: solution times remain relatively low; the number of demand nodes assigned to a site other than the nearest site is often very small; and the cost penalty paid for assigning demand volumes to the nearest facility as opposed to assigning them optimally is only a fraction of a percent.

4.4 The Strategic Network Design Tool and Description of Experiment

In making decisions concerning the strategic network design and identifying decision opportunities, quantitative tools that measure supply chain performance in terms of cost, profit and service level play a major role. The research behind this dissertation developed a tool called *SNDOptimizer* that allows the user to address the network design problem for multi-echelon supply chains. The application is written in the C-Sharp programming language. Supply chain optimizers normally offer the capability to construct a graphical user interface and the ability to connect with the optimization engine. Figure 4-8 illustrates the general methodology of the optimization procedure and interaction between tools.

The *SNDOptimizer* tool focuses on facility location and customer allocation problems. Metaheuristics are primarily used as an engine for solving the mixed non-linear integer problem. It is possible to choose two metaheuristic approaches implemented by the platform *SNDOptimizer* to solve problem instances. Furthermore, it can import data from general database systems and spreadsheets like MS-Access and MS-Excel. In particular, data for multi-echelon supply chain problems include Plants', Warehouses', Candidate DCs' and Customers' information. All input data can be saved and opened as part of one project that is associated with an instance of the problem. *SNDOptimizer* automatically generates an instance of the problem and tries to solve it by the application of its solver. For planning and analysis for actual implementation, the tool supports graphical statistical outputs that are necessary to capture the value of the optimal solution. This tool provides the following as optimized output:

- The location for each open DC.
- The customer-to-DC assignments.
- Optimal order quantities for each open DC
- Demand levels satisfied at each open DC
- Detailed cost summary for each open DC

A typical network configuration problem involves large amounts of data. To design an integrated supply chain, the decision-maker needs to have information on at least the following items (Shen, 2005):

- locations of customers and the candidate locations of Distribution Centers (DCs)
- information (e.g., annual demand) about different products
- cost parameters of opening and operating DCs, inventory, and transportation

For facility location and demand allocation problems, the geographical parameters, base cost parameters and base constraints form an adequate input data set. The model includes the current network of central warehouses, potential distribution centers, and retailers that respond to consumer demand for finished goods SKUs.

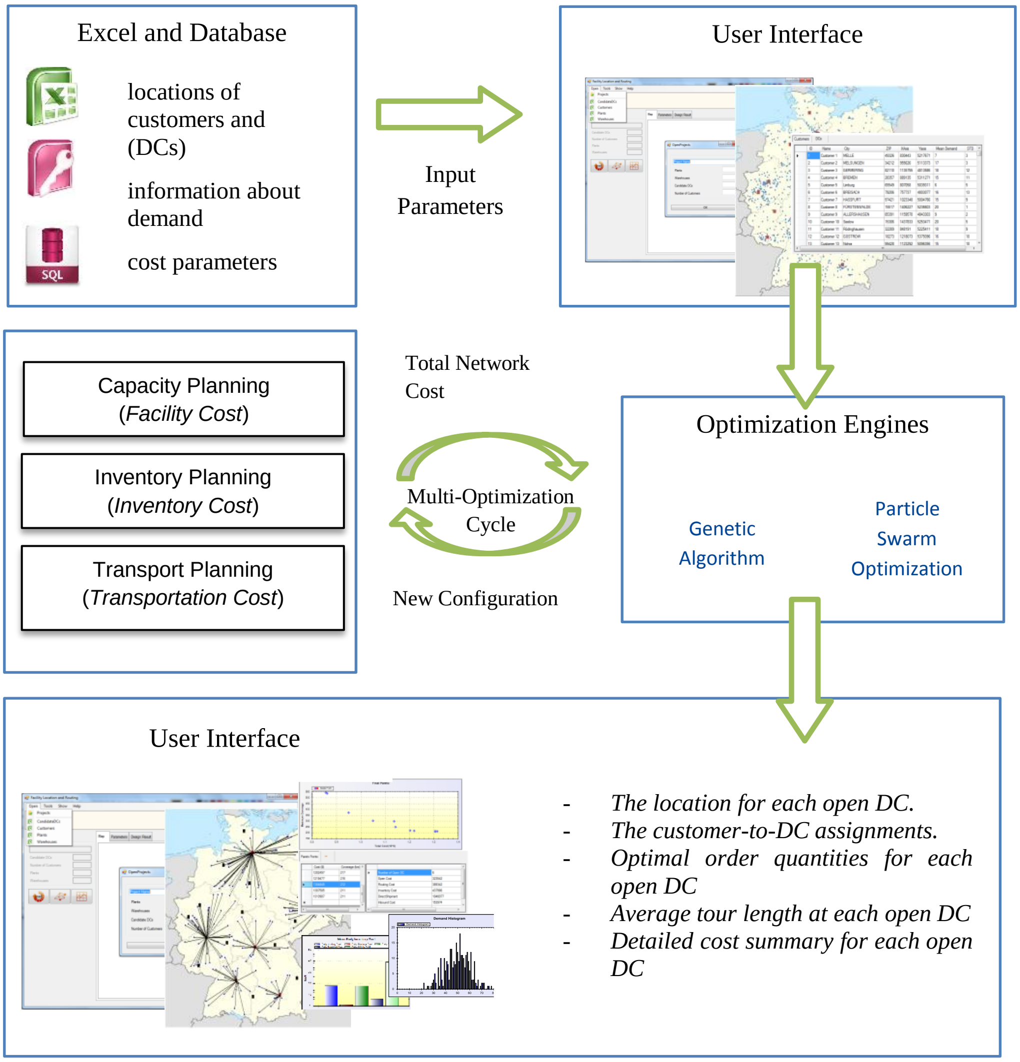


Figure 4-8: Structure of a supply chain network optimizer

4.4.1 Description of Strategic Network Design Experiment

This section presents a significant case study that deals with a real distribution network problem faced by a large national distributor. The company is located in a European country, produces three major brands of products, and holds more than 3,000 different SKUs per day (stock keeping unit). Its network includes several production locations (plants), several central warehouses to supply the multiple distribution centers (20 potential locations) of various retail companies and approximately more than 1000 a large set of geographically scattered retailers and customers. In such a network, products are transferred from plants to their warehouses, from warehouses to DCs, and from there, to retailers. It should be noted that warehouses are located at the plants.

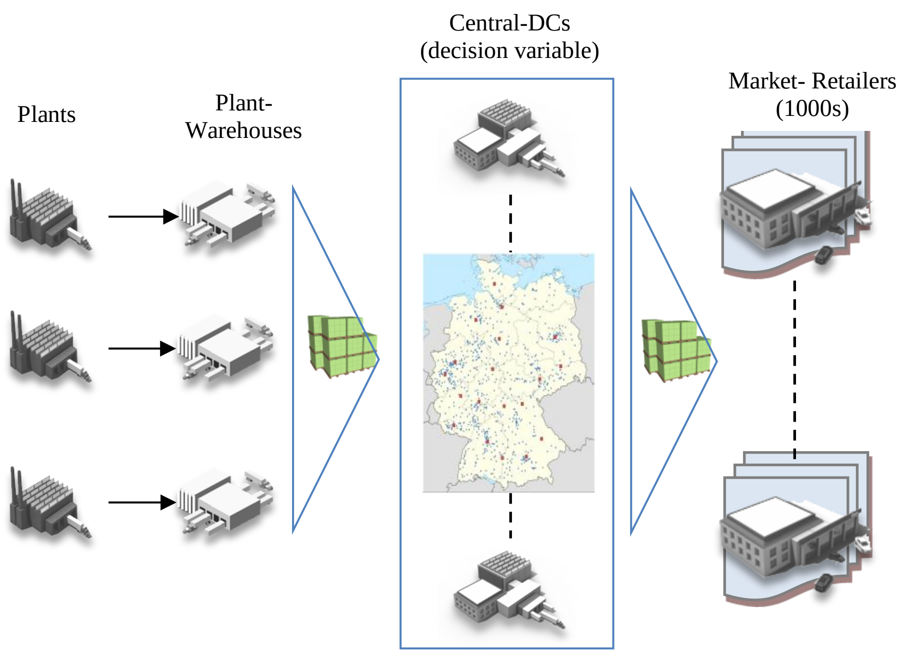


Figure 4-9: Supply Chain distribution network of the case study

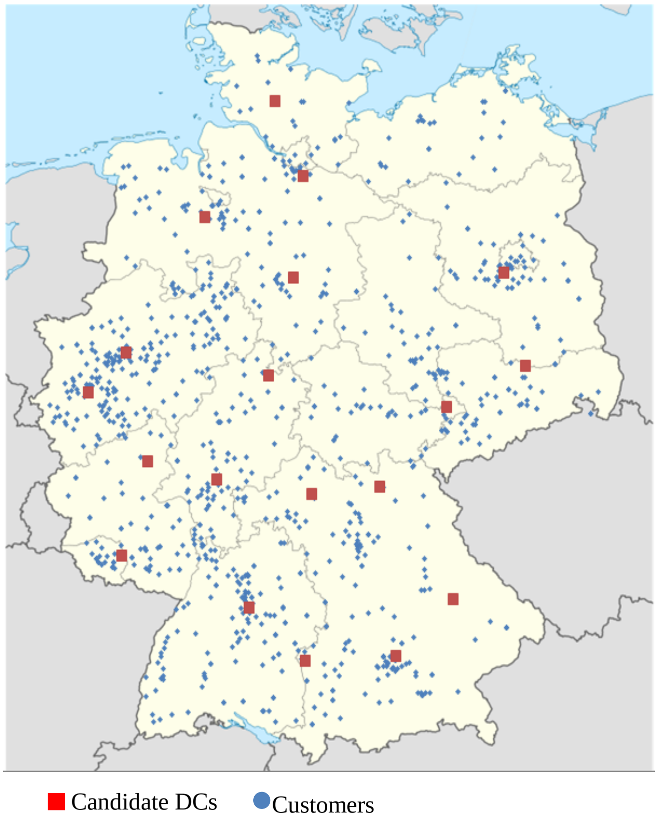
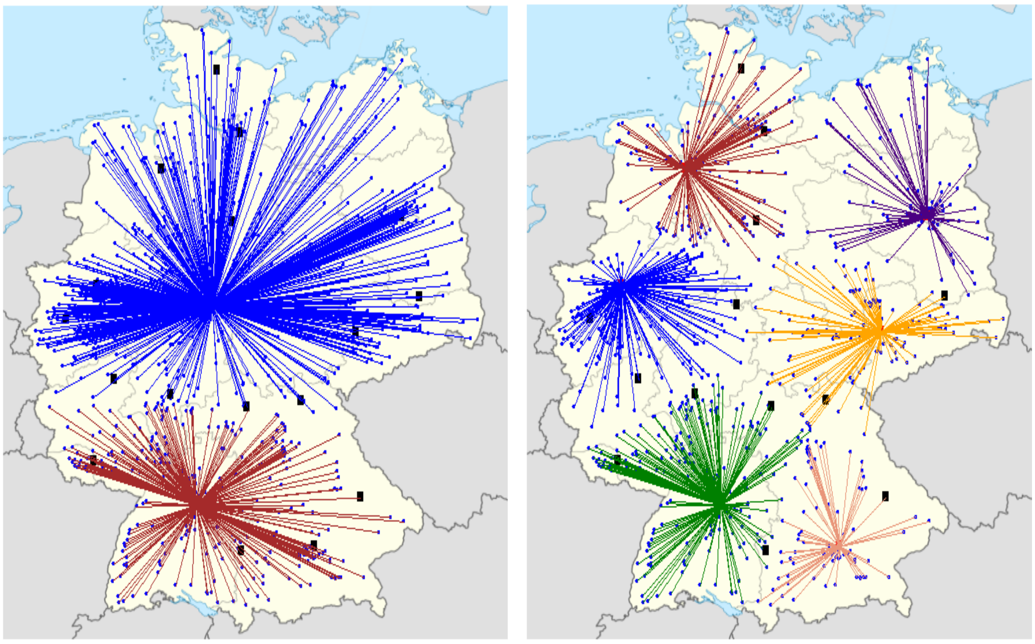


Figure 4-10: Candidate DCs and customers' location

It is assumed that the warehouses replenish multi-items from infinite supply plants and act mainly as transition points, i.e., no inventory is held at the warehouses. The distribution centers hold stocks of multi-items to help consolidate shipments and deliver them to their customers (or retailers). DCs use common inventory policies to replenish their inventory levels. Each distribution center faces a stochastic customer demand from stores who carry negligible inventory of the products. Figure 4-10 illustrates the geographic location of candidate DCs (red square dots) and the location of demand points (blue circle dots). The main question is to find the optimal number, size, location, and service area of facilities that minimize the costs and maximize service efficiency to serve the customers.

4.5 Model Results

The goal of this section is to show the application of the mathematical model by numerical results obtained by solving instances of the location-inventory problem as a practical case study and to highlight several insights in response to varying the parameters. For each experiment, it is examined that how the network design decisions change with variable test parameters. These test parameters include the number of customers in the system, the average unit inventory holding cost, and the average unit transportation cost per km. All other parameters are considered common parameters and remain constant for all sample problems and the experimental data used is defined in Appendix D. All computational work was performed on a personal computer (32-bit operating system, 2.70 GHz CPU, and 8.00 GB.



Cost: 2 610 228 €
Coverage Distance: 432 km

Cost: 3 049 635 €
Coverage Distance: 221 km

Figure 4-11: Location-Allocation Result of Integrated Network Design

A typical experimental result for two optimization criteria incurred in designing the distribution network is illustrated in Figure 4-11. The red squares represent DCs used in the solution as the black squares represent DCs that are located not to open. Allocation of demand to the corresponding DCs is shown with straight line. From the observed result, the cost is measured in 2,610,228 € for minimum cost criteria, while the cost is measured in 3,049,635 € for minimum coverage distance criteria. Figure 4-12 shows all the solution points in the Pareto front line that are found by minimizing the total cost while decreasing the maximum distance between uncovered demand and opened DCs. For example, it can be seen in the figure that two DCs are finally selected for minimizing cost, while 6 DCs are required for minimizing the maximum customer coverage distance. From the Figure 4-12, it can be also seen that for the cost values between 2,610,228 € and 3,049,635 € result in maximum coverage ranging between 432 km and 221 km. Figure 4-13 shows the difference in performance for each cost component, based on the solutions with 2 DCs and 6 DCs opened. Clearly, and supported by the results, it can be seen the impacts of two decision criteria on the cost components and the number of the DC selection. Figure 4-14 illustrates the solution points of the model in terms of the trade-off between coverage and cost. According to Figure 4-14, a 48.84 % reduction in coverage distance is offset by a 16.83 % increase the total cost. It is worth mentioning solution 9 and solution 10, a 13.2 % reduction in coverage distance can be offset by a 0.1 % increase in total cost. The trade-off between coverage distance and cost provides a guideline for decision makers in selecting an efficient solution generated from a multi-objective facility location model.

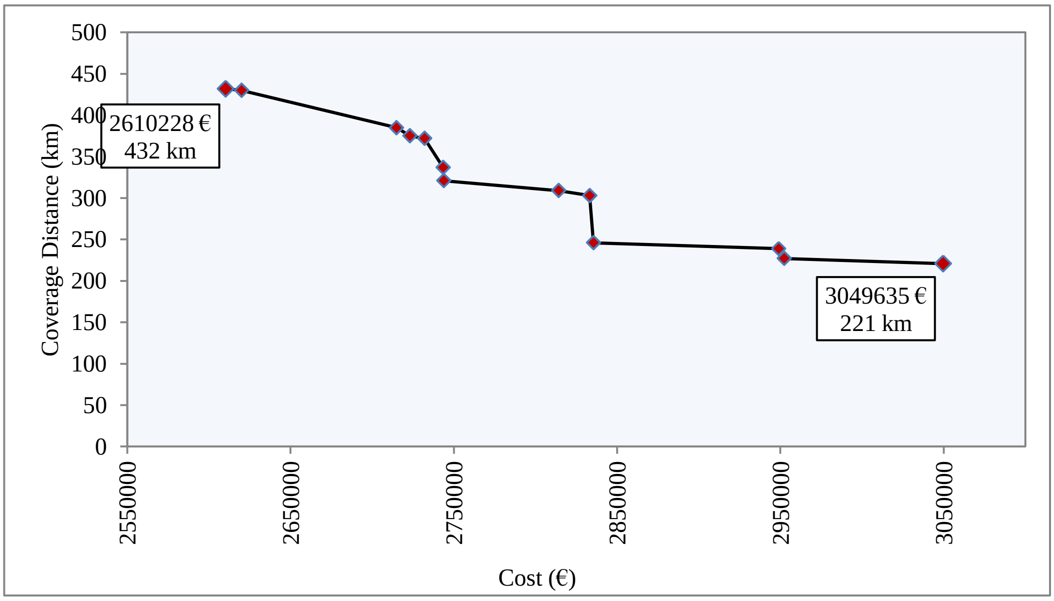


Figure 4-12: Non-dominated solutions of the model — first objective is to minimize the total cost and second objective is to minimize the distance between uncovered demand and opened DCs

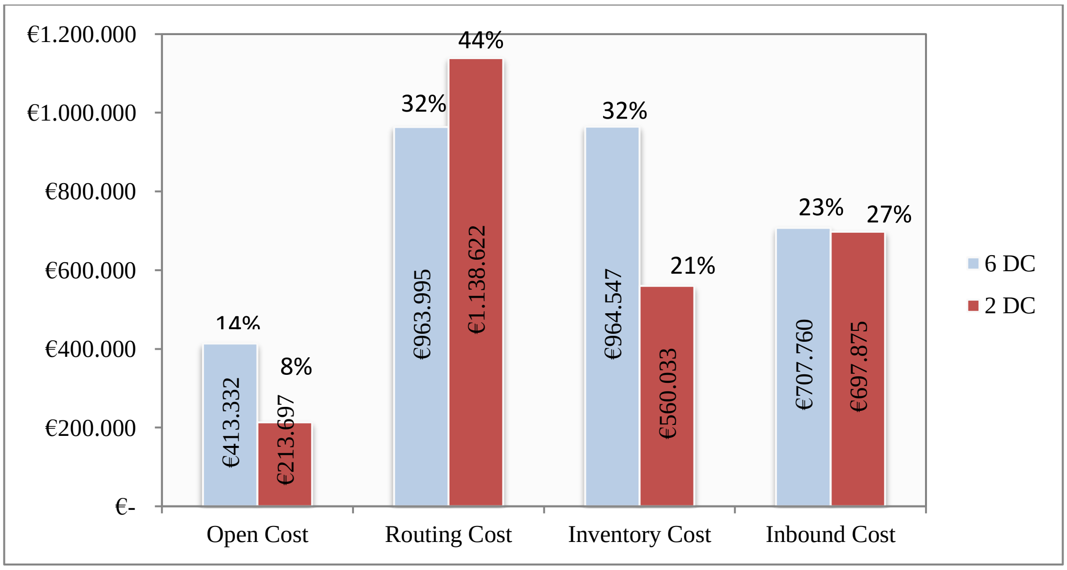


Figure 4-13: Cost components performance comparison for the two configurations

To evaluate the influence of transportation and inventory costs factors on DC selection and customer assignment, the values of β (weight factor for inventory cost) and θ (weight factor for transportation cost) are varied. To analyze the ratio between the unit transportation cost and the unit inventory cost, the case study scenario is modeled with 200 customers. Changing the weights of the costs leads the model to present a new optimal design, which is depicted in the Table 4-1.

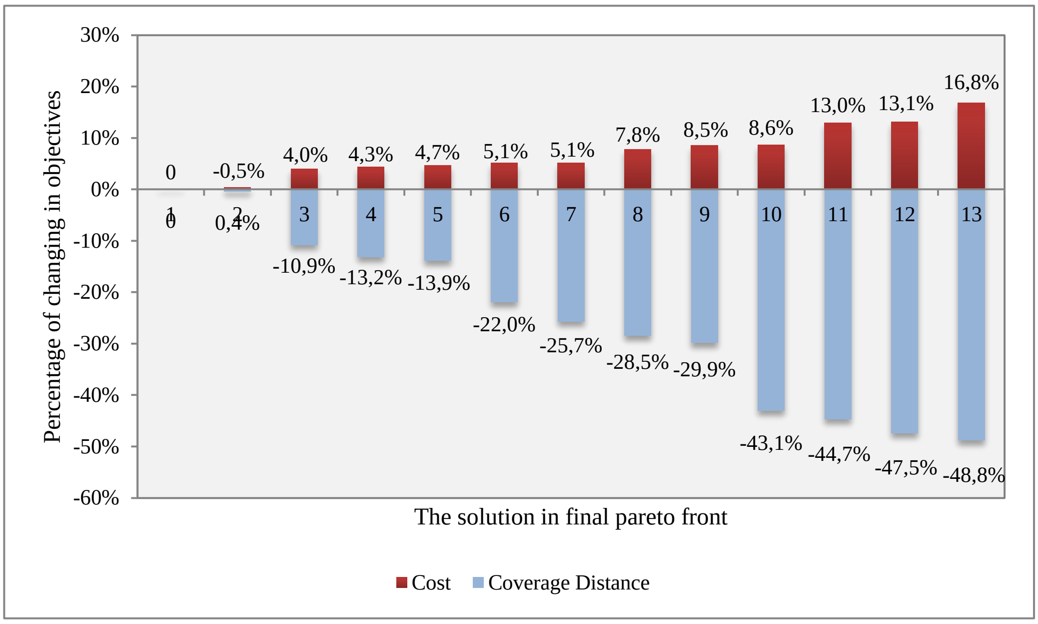


Figure 4-14: The trade-off between the cost and coverage distance

It is observed from the computational result based on the objective of cost minimization that as the proportion of transportation cost goes up, the number of open DCs increase. Increasing θ will increase the impact of the sum of location and transportation costs versus inventory costs. As transportation cost becomes more important, the number of DCs increased. On the other hand, as β increases, the number of DCs decreases in order to take advantage of the collective safety stocking effect. Optimal solutions obtained from the Pareto front of efficient solutions based on two objective functions are illustrated in Figure 4-15 under integrated and non-integrated scenarios.

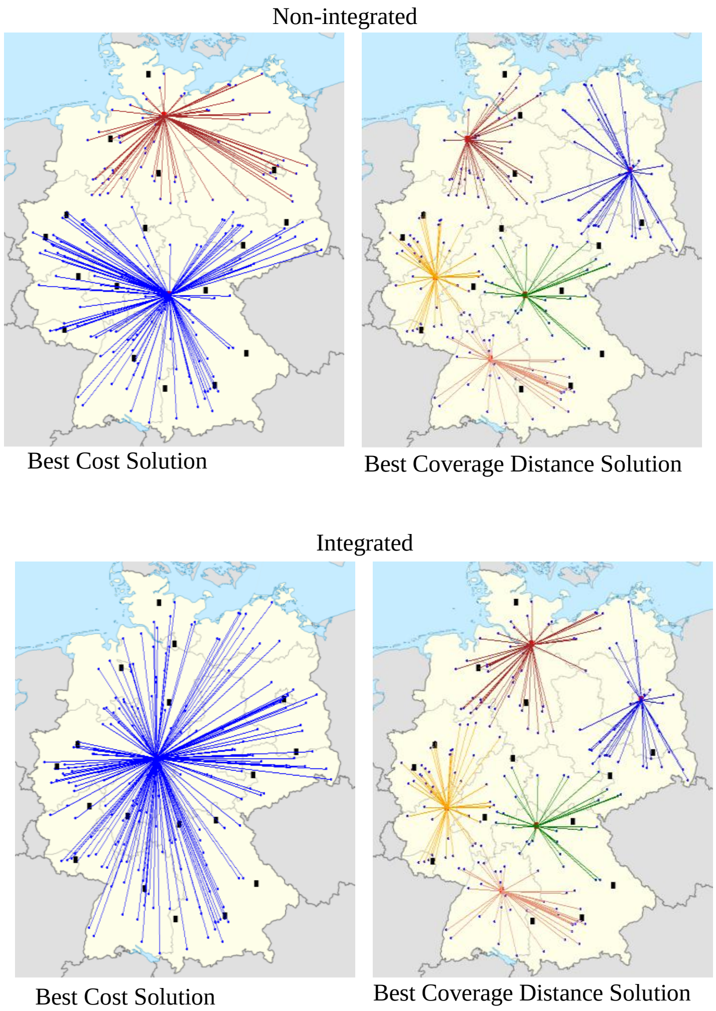


Figure 4-15: Comparison of integrated and non-integrated (without inventory cost) network design

According to the Figure 4-15, as cost minimization has an impact on the number of opened DC, the coverage distance objective has not an impact on the best solution. To evaluate the efficiency of the proposed algorithm, a comparative test was performed with multiobjective genetic algorithm (NSGA-II). NSGA-II (Elitist Non-Dominated Sorting Genetic Algorithm) is one of the most popularly used GA for multi-objective optimization. The testing network consists of 200 customers and 20 candidate distribution centers (DCs). For implementing GA, population size of 100 is taken and the maximum number of generations is taken as 100. Uniform crossover is used as the recombination operator. As illustrated in Table 4-2, MO-QPSO is faster than NSGA-II for the average computational time.

Table 4-1: Computational results of varying weight factors

θ / β	Open DCs	Open Cost	Routing Cost	Inventory Cost	Inbound Cost
1	3 DCs	3%	67%	5%	25%
0,5	2 DCs	4%	65%	8%	23%
0,1	1 DCs	9%	53%	21%	17%

Table 4-2: Solution times of different problem sets

			NSGA-II	MO-QPSO
Problem Set	No. Of Customer	No. Of candidate DCs	CPU Time (millisecond)	CPU Time (millisecond)
1	50	10	12030	3933
2	100	10	47029	15004
3	100	20	59462	22596
4	200	20	184853	112368

4.6 Summary

In this chapter, the facility location problem has formulated as a mixed nonlinear integer programming model that takes into consideration nonlinear facility location costs, inventory costs and routing costs. Most of supply chain network designs in previous literature focused on minimizing total costs only. In real world problems, however, there are multiple objectives to be considered simultaneously and they are typically conflicting objectives. Thus, two objectives have been considered in this study. The one objective under consideration is to find the best number and location of DCs that minimizes total logistics costs. The second objective is to minimize the maximum distance between each covered customer and its closest opened DC to maximize demand satisfaction in a defined structure. As with most combinatorial problems, exact methods are limited in the size of the problem that they are able to solve within reasonable time. For larger instances, it is therefore necessary to use faster heuristic methods. Consequently, due to the complexity of the problem, optimization process of the mathematical model has been performed using metaheuristic algorithms. Quantum-based Particle Swarm Optimization (QPSO) technique has been applied as a solver to find the Pareto optimal solutions.

The proposed model provides an insight into the simultaneous relationship between facility location, inventory, and transportation. All the results tend to highlight that the distribution network design in the real world may be better analyzed when considering the interdependence between decision levels rather than considering each decision level individually. It has been also observed that the optimal network structure is quite different with (integrated) and without (non-integrated) considering inventory in the supply chain design. In this chapter, a strategic network design tool (SNDOptimizer) has been presented for the purpose of solving the multiobjective integrated supply chain problem. The proposed approach and models implemented by SNDOptimizer developed in C-Sharp to find feasible solutions closed as possible to the optimality.

Chapter 5

Object-Oriented Modeling for Inventory of Multi-Echelon Supply Chain

In recent years, the efficient and effective management of material flow throughout the supply chain has become more important in order to improve customer service level and reduce costs for the whole system. In the past, the majority of the solution approaches used to solve multi-echelon supply chain problems were based on conventional methods using analytical techniques. However, they are insufficient to cope with the SC dynamics because of the inability to handle to the complex interactions between the SC members and to represent stochastic behaviors existing in many real world problems. Unlike the traditional methods, simulation has recently become a major computer-based tool that enables us to model complex systems without limiting assumptions, which are subject to both variability and complexity (Banks, 2000). This chapter describes the design of an object-oriented simulation framework to analyze different inventory control strategies within a given supply chain. The primary objective of this chapter is the development and creation of a multi-echelon supply chain simulation framework primarily for use in inventory applications. A secondary objective is to describe an overview of how an object-oriented library for simulating inventory is implemented. The simulation toolbox is developed using Microsoft Visual C-Sharp programming language, which is one of the several languages that support object-oriented programming. The library classes consist of objects representing the nodes, an interconnection structure for a multi-echelon system, and a management system for moving the material between different nodes within the network. A brief description of different simulation modeling approaches is presented in Section 5.1. Section 5.2 presents a conceptual model to describe inventory processes of multi-echelon supply chains. The details of the proposed object-oriented simulation model are given in Section 5.3. Section 5.4 presents the cost components of the simulation model.

In Section 5.5, we describe the performance measures identified through simulation.

5.1 Major Supply Chain Simulation Approaches

In today's business environment, supply chains are faced with challenges to deliver high quality products and to bring products to the customer on time to achieve a competitive advantage. Demand variance, uncertainties in lead-time, forecast errors, and a dramatically changing production environment make supply chains more complicated to analyze. Developing a model that represents the supply chain characteristics and dynamics is an important issue to understand the mechanics and processes of a supply chain (Ramakrishnan & Wysk, 2002). In the literature, modeling of SC is classified into two main categories: analytical models and simulation models. According to Min and Zhou (2002), supply chain models can be classified as deterministic (non-probabilistic), stochastic (probabilistic), hybrid, and IT-driven. On the other hand, Sabri and Beamon (2000) classify supply chain modeling into four groups of deterministic analytical models, stochastic analytical models, economic models and simulation models. Since many analytical models are inadequate for the realistic representation of the system due to the fact that they lack the capability of handling variability and uncertainty, simulation is used as an effective way to model the supply chain because of its ability to incorporate uncertainties and dynamics of supply chain.

Recently, simulation has been considered as a decision support tool offering an alternative method for detailed analysis of the complex real world systems and is defined as a representation of a real system that usually takes the form of a set of assumptions concerning the operation of that system (Banks, 2000) (Douraid et al., 2012). There is several simulation methods used to study the dynamics that result from decisions made in such systems. In this context, four simulation types are distinguished by Kleijnen (2003): spreadsheet simulation, system dynamics (SD), discrete-event simulation (DES), and business games. Although the object-oriented simulation framework is chosen in this study, this section first discusses four common simulation methods known as spreadsheet simulation, SD, DES and agent-based simulation (ABS).

5.1.1 Spreadsheet-Based Simulation

Spreadsheet simulation refers to the use of a spreadsheet to represent the model and perform the simulation experiment (Seila, 2001). This kind of simulation is quite suitable for the user and an attractive platform for simulation, since developers and users can easily pass simulation models to one another. However, assessing the results of proposing these simulation models with spreadsheets may prove too simple and unreal (Kleijnen & Smits, 2003).

5.1.2 Systems Dynamics Based Simulation (SDS)

System dynamics is a computer-aided approach to study and manage complex feedback systems like one finds in business and other social systems (Márquez, 2010).

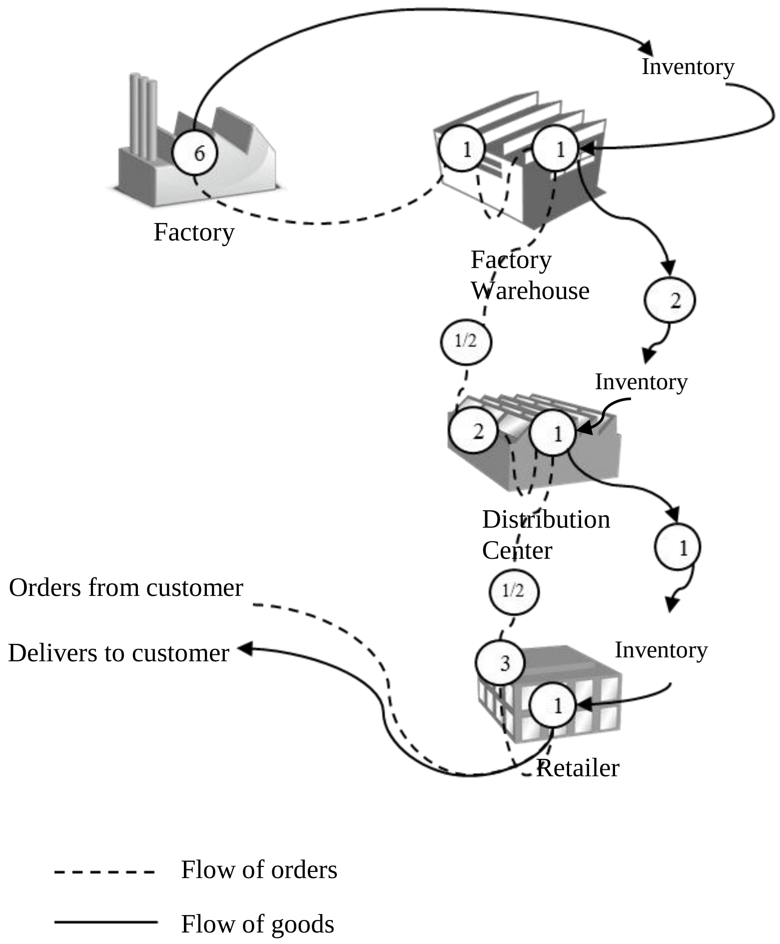


Figure 5-1: Forrester's Supply Chain Dynamics Model (Forrester, 1961)

Forrester first applied system dynamics to industrial management problems in the early 1960s as a modeling and simulation methodology. The classic supply chain model used by Forrester is divided in four levels: retailer, wholesaler, distributor and manufacturing as shown in Figure 5-1. (Forrester, 1961). He studied how these links react to deviations between the current inventory levels and the target inventory levels. He found that 'common sense' strategies may amplify fluctuations in the demand by final customers up the SC (Kleijnen & Smits, 2003). In general, the main advantage of system dynamics (SD) is providing very effective modeling and analyzing complex dynamics affected by non-linearity, feedback loops and time delays, which significantly impact the behavior of the whole system (Sterman, 2000). However, variables in SD models are generally usually represented as deterministic average values (Tako & Robinson, 2006).

5.1.3 Discrete-Event Simulation (DES)

Another widely used simulation technique is discrete-even simulation (DES). The use of DES for strategic, tactical and operational problems in manufacturing, logistics, and supply chain management has grown in recent decades. It has been used widely for network optimization, policy optimization, identification of the causes of uncertainties and their impact, and in the development of methods to reduce/eliminate these uncertainties (Ramakrishnan & Wysk, 2002). In DES, the simulation model has a given state at any point in time, and the simulation state remains unchanged unless a simulation event occurs (Altiok & Melamed, 2007). Each event is implemented as a procedure (computer code) whose execution can change state variables and possibly schedule other events. Main challenges in DES that supply chain analyst faces are (Lee et al., 2002): i) reflection of the continuous nature of the process is not possible, ii) growing complexity for more detailed models, iii) too much simplification for small scaled models.

5.1.4 Agent-Based Simulation (ABS)

Recently, Agent Based Simulation (ABS) has been increasingly used to analyze business systems and supply chain management as a new modeling paradigm. In ABS, the model consists of a set of agents that represent the behaviors of the different individuals or entities within the supply chain network, e.g. customers, retailer, wholesaler, manufacturer, supplier or any other entity (Tah, 2005). In order to satisfy its own objectives, each agent has its own behaviors or algorithms to make its own decisions, a number of parameters or indicators to express its status (Sarker et al., 2005). For example, a retailer (an agent) determines its market demand, calculates its own ordering quantity, places orders, receives products from the distributors, updates its status, calculates cost and sells to the market. According to Kodia (2010), the main advantages of the agent based simulation can be summarized as follows: i) it considers individual behavior, ii) takes into account actions and interactions between individuals, and iii) examines the emergence of collective phenomena.

5.2 Object-Oriented Framework for Multi-Echelon Inventory Simulation

As mentioned in the previous section, supply chain modeling commonly implies simplified representation of the system with components or building blocks. To facilitate the modeling and analysis of different supply chain settings, an inventory simulation library is developed using an object oriented programming language that implement a set of suitable object classes. These classes are used as building blocks and a subsystem that can encapsulate a large number of system parameters within given instances. The class diagrams of the simulation framework in details are illustrated in Appendix B. The traditional approach in the simulation of a supply chain is to define the system as a network of different nodes (i.e., factories, warehouses, retailers and customers) and each of these nodes performs different functions. A link between nodes represents the flow of materials and information among the whole supply chain that makes possible the functions of procurement, processing (or manufacturing), storage, and distribution (Beamon & Chen, 2001). In the developed simulation framework, different object classes are defined to represent each type of node in the supply chain, such as customer class, retailer class, warehouse class, and factory class. Figure 5-2 and Table 5-1 provide a brief description of important classes in the presented simulation framework. This class hierarchy can be extended in many ways. Customer, which is at the lowest in the supply chain network, is an object class that represents the source of the original downstream demands. Factory is an object class that is responsible for transforming raw material into intermediate or finished products. In general, a factory receives orders from the warehouse. The main activity of the warehouse class is to manage storage and handling processes, and the retailer class is where an external customer buys the product. Transportation class represents the link between nodes, which is used to move product from one node to another in a supply chain. Every class object sends demands or order requests to the next class object in the upstream direction and ship products to the node that is downstream in the network. At the end of the simulation, every object related to inventory computes the service level and costs of the current scenario and adds the result to the value of overall costs. The following sections will discuss the classes within the inventory simulation tool.

Table 5-1**:** List of classes in supply chain simulation framework (Güller et al., 2015)

No	Class Name	No	Class Name
1	SupplyChainMap	11	Retailer
2	Simulation	12	Warehouse
3	Clock	13	Factory
4	Time	14	Transportation
5	NodeEventAbstract	15	Location
6	ArrivalEvent	16	Statistics
7	OrderEvent	17	Inventory
8	StockPointAbstract	18	InventoryPolicy
9	Customer	19	Parameters
10	ProductionPolicy	20	QueuePolicy

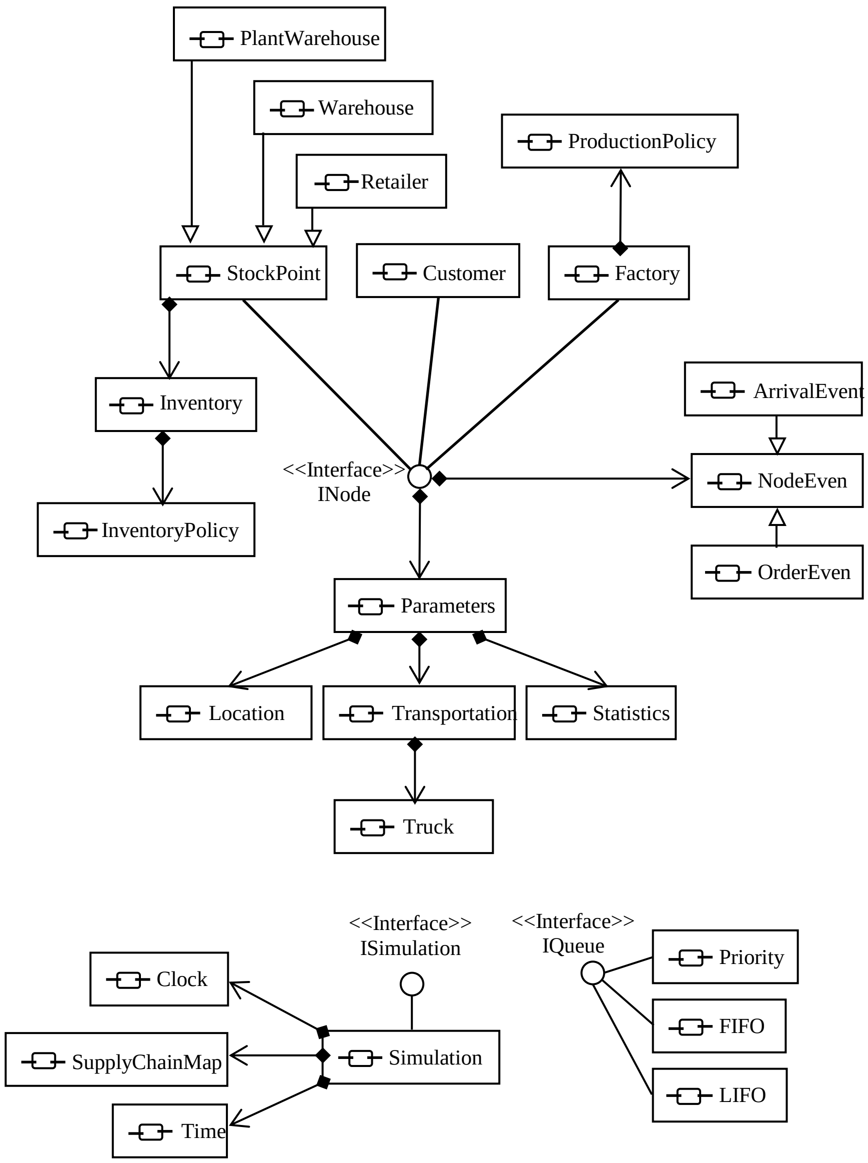


Figure 5-2: UML class diagrams of simulation package (Güller et al., 2015)

5.3 Some Object Classes for Simulation of Multi-echelon Inventory System

The object-oriented approach is one of the popular modeling techniques to design and simulate complex systems. According to Barcio (1996), the main advantages of using object-oriented techniques in modeling and simulation are: *"(i) software reuse is enhanced when object-oriented techniques are applied efficiently in defining the system objects, (ii) objects in the system can be defined in close correspondence to real-world objects, (iii) the rapid development of new software is promoted, (iv) the use of inheritance enables the creation of new objects and associated methods with minimal effort, and, (v) the use of encapsulation provides the appropriate distinction between object boundaries and is effective in identifying and controlling the propagation of errors*". The general principle of Object Oriented Programming (OOP) is to formulate problem using interacting objects rather than a set of functions and to define these objects in terms of their attributes and methods (Güller et al., 2015) (Alfons et al., 2010). In OOP, objects are categorized into classes and class hierarchies. The behavior and interactions of these objects are modeled with generic functions and methods (PressMan, 1997). Each supply chain members in the object-oriented framework of the multi-echelon system, such as supplier, factory, warehouse and customer, can be modeled independently from the coordinating simulation tool. Hence, object-oriented design makes it easier to customize individual elements, thereby allowing more flexibility in the design (Richardson, 2006). The most important concepts in OOP supporting the design of such systems are encapsulation, class inheritance, subclasses, and polymorphism (PressMan, 1997). Inheritance provides defining new classes from existing classes and allows inheriting the attributes and methods of their base classes to the new classes (Garrido, 2009). In addition to the attributes and operations shared with base classes, subclasses (derived classes) can be defined by additional features. The encapsulation principle refers to information and the attributes of an object hiding and is considered as a protected mechanism with an imaginary protection wall. Hence, all data and functions in a class are protected from any unauthorized access.

The specification of the object-oriented framework of a system begins with the identification of the key elements within the system, their roles, attributes, relationships with each other, and modeling and implementation issues (Rosetti & Nangia, 2007). The main packages needed within a generic inventory simulation in the framework are the following: *Event*, *Node*, *Queue*, *Simulation*, and *SupplyChain* summarized in Table 5-2. Since it is beyond the scope of this section to discuss in detail the implementation of packages and all classes, a brief description of important classes is provided in this chapter.

Table 5-2 Supply chain inventory simulator packages

Package	**Functional Description**
Node	Classes that represent locations within the supply chain, such as a warehouse.
Event	The package consists of a collection of event classes, such as customer arrival, transportation, and order processing. Each event objects change a state and is responsible for scheduling other events that depend on that event.
Queue	The package consists of different kind of queue logic such as FIFO, LIFO and priority list.
Simulation	The package responsible for the scheduling and execution of simulation events.
SupplyChain	Classes represent the connections between nodes and structure of SC

According to Biswas and Narahari (2004), the elements of the object library in a simulation model of multi-echelon supply chain can be classified into two categories: structural objects and policy objects. Whereas the structural objects define the physical entities of the network, the policy objects define the protocols used in logistics processes such procurement, manufacturing, transportation, and distribution (Biaswas & Narahari, 2004). The main classes of the structural object in the presented simulation framework are factory, warehouse, retailer, supplier, customer and vehicles. Table 5-3 illustrates the responsibilities of these objects.

Table 5-3 Main supply chain structural objects and entities (Biaswas & Narahari, 2004)

Customer	A customer can be either an internal customer that is the various entities of the network like the plants and the distributors or an external customer that is the consumers of the products (finished or semi-finished). This class may also contain information related to demand data.
Supplier (Factory)	A supplier provides a plant with raw materials or sub-assemblies. A supplier could be a manufacturing plant or a late-customization center or a full-fledged supply chain.
Retailer	An external customer generally buys the products from the retailer. A retailer has an associated stocking warehouse, where the inventories of the products are stored. A retailer can receive deliveries from distributor or plant central warehouses or late-customization center or from some other retailer. The product is delivered to customer if it is available in the retailer's warehouse. Otherwise the order is added to a queue for the particular product, according to a pre-assigned priority. The order is delivered when the product is received (from distributor or plant or late-

	customization center as the case may be).
Warehouse	A warehouse is a storage facility that is characterized by the nature and capacity of the products it can store. It can be attached to the plant, the distributor, and the retailer.
Vehicle (Truck)	Vehicles transport products from one node of the network to another. Each vehicle has characteristics in terms of products it can carry, capacity (in volume or weight), costs, and speed.

5.3.1 The **Simulation** *Class*

To manage the simulation experiments and communicate with the optimization tool, a general control class, called *Simulation*, is utilized in this thesis. The *Simulation* class contains the definition of parameters that might be necessary within a simulation such as the period, number of nodes, location of nodes etc. (Güller et al., 2015). This class maintains a simulator's clock recording the current simulation time and the next event that is retrieved from the event list, and starts executing the events in the appropriate order. Its methods serve to trigger the clock for simulation, stop the simulator's clock, initialize the simulation, and read the simulation clock. One of methods used in this class is the *Run* method that starts the execution of simulation based on the desired number of replications and run length. The simulation process continues until some pre-specified stopping condition or no more items are on the event list. The parameter *simulationPeriod* defining the duration of a simulation experiment is a user-defined value. Execution ends with the creation of a *Statistical Results* window.

5.3.2 The **NodeEvent** *and* **Queue** *Classes*

The abstract class *NodeEvent* is being used to represent the collection of processes (events) related to the flow of material through a supply chain. Events are the result of a structural object's action and are processed from the environment simulator. Each type of event should be defined as a subclass of the *NodeEvent* class. The fundamental constructed events in the library, occurring at supply chain members, are "order event" and "arrival event" (Güller et al., 2015). The main recorded data in such an order event are the quantity of ordered item, type of the sender and the receiver, and time properties associated with this event. When an order event is constructed, it is scheduled based on the duration of process and current simulation time. Arrival event is the process of accepting an order that has been filled.

During the simulation run events are sorted on a time axis in increasing order of simulation clock time. For this purpose, the *IQueue* interface is created with some queue policies, e.g. FIFO, LIFO and priority. According to the selected policy, the event list is sorted from top to bottom by ascending time or ascending priority in order to select future event to execute. As a result, the *Queue* class provides a mechanism to select events from the future event queue.

5.3.3 The **StockPoint** *Class*

The *StockPoint* abstract class and interface *INode* that encapsulates logistic activities are used to model the member of a supply chain that hold stocks, such as warehouses and retailers. User-defined stock point classes must be declared as extensions of the *StockPoint* class and *INode* interface. The class structure consists of the data declarations that will define the characteristics of the objects created from this class. Examples of *StockPoint* methods that are responsible for the functions and data related to the inventory are *CheckIniventory(), StockGeneration(), MakeReplenishment(),* and *Initialize()*.

5.3.4 The **Customer** *Class*

When dealing with modeling a supply chain, one of the most important issues is to define customer demand structure. The *Customer* class is an object class that is responsible for the functions and data related to the end-customer of a supply chain network. The *Customer* class generates the sampling of random demand by providing details of the customer requirements within the system. The demand inter-arrival time (or demand per unit time) and demand order sizes require three inputs: distribution, mean, and coefficient of variation (CV) or standard deviation. Distribution related to demand can follow either a discrete or continuous distribution. The normal distribution assumption is known to be a very good fit to describe many demand functions at the different levels of supply chains for the cases of fast-demand items. However, for very slow moving items, it is usually assumed that the demand process is Poisson distributed. A large number of studies assume a homogeneous normal distribution demand pattern in supply chain problems because of its convenient mathematical properties. However, actual customer demand may be better modelled with distributions that are asymmetric and positive skew shape (Cobb et al., 2013). Thus, the lognormal distribution is more suitable than the normal distribution when modelling non-negative demands (Juan et al., 2014). As a result, Gamma, Beta and Lognormal distributions have been found to be of considerable value in describing demand functions. For simplicity, customer demand is generated as accumulated demand per day, per week, per month, etc.

5.3.5 The Retailer *Class*

The *Retailer* class is an object class which represents a member in SC. The new *Retailer* object inherits from abstract class *StockPoint* and deals with external customers, but also deals with suppliers.

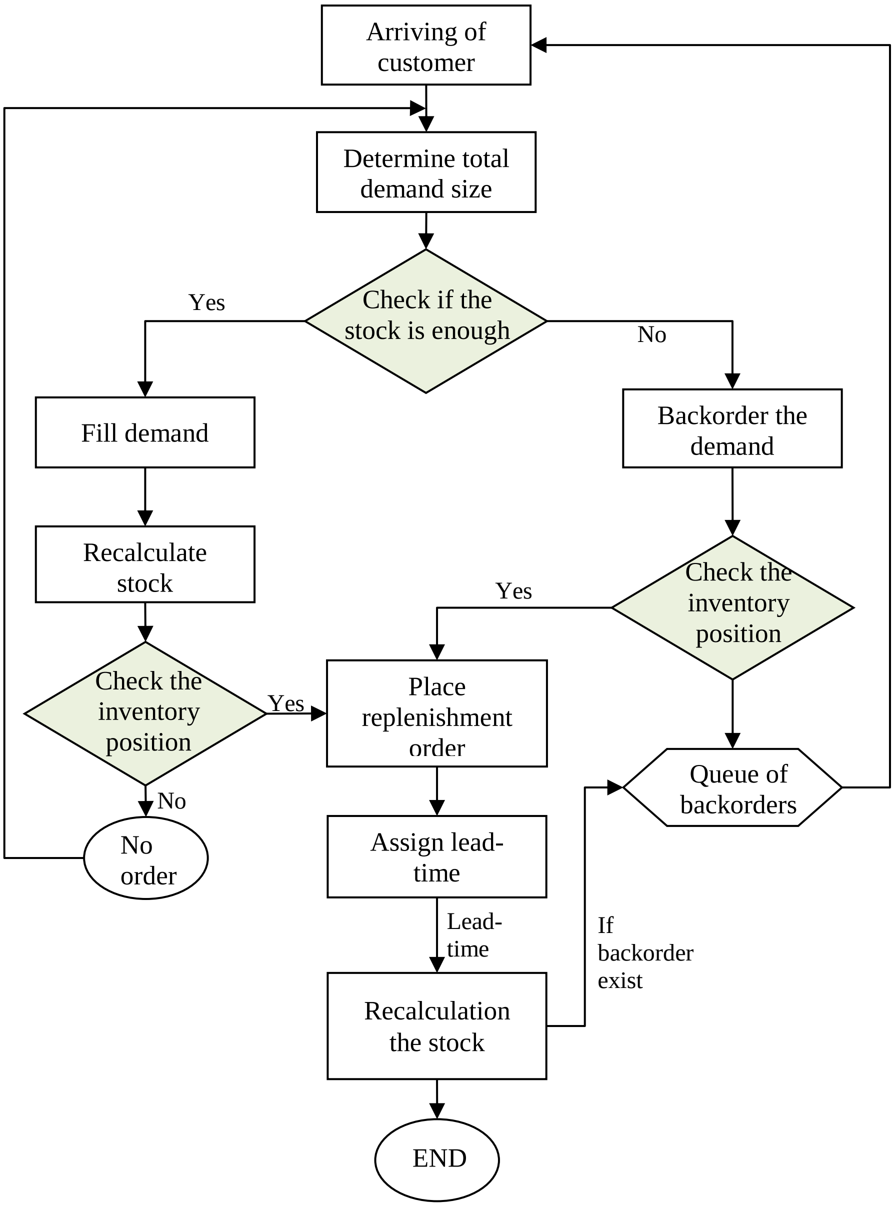


Figure 5-3: Flowchart of (R, Q) Inventory Policy for Retailer Class

The retailer object receives demands from the instance of its external customer as an input and places orders for stock replenishment based on inventory control policy to its supplier as an output. If a demand is received through the customer, the object tries to satisfy the demand as soon as possible. If the amount exceeds the current inventory level, the demand is backordered, and inserted into a list called *BackorderItems*, which corresponds to a waiting queue for unsatisfied demands. The demand does not allow partial filling. Accumulated backorders in a queue are satisfied on the queue rule after the arrival of a replenishment order. The retailer objects are characterized by a list of parameters such as replenishment policy, leadtime, fixed order costs, stock holding costs, shortage costs, delivery costs, etc. For the purpose of supply chain inventory simulation, an inventory (replenishment) policy is assigned to a certain retailer object. Based on the inventory policy, the retailer places an order to its supplier (or its warehouse), whenever the inventory position goes below the predefined reorder point. An overview of the inventory control logic of retailer object is shown in Figure 5-3.

5.3.6 The **Warehouse** *Class*

This class models the warehouse, which is one of the structural objects of a supply chain. Warehouses, which are connected to the supplier and the retailer, go through a process of receiving products from the supplier, storing them and sending them to the retailer. The same architecture of the retailer class is implemented for the warehouse class with some different variables and modified methods. Objects of this class have an input to receive orders for products from retailers and an output to send requests to its suppliers. The two main logics implemented in warehouse objects are supplying retailer orders and controlling inventory.

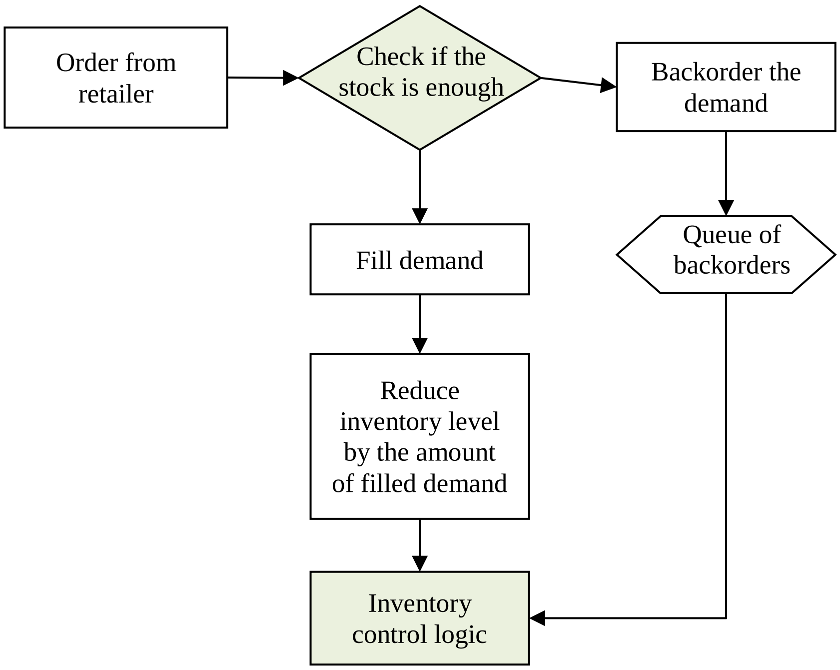


Figure 5-4: The supply operation flow chart for warehouse class

As described above the whole supply chain network is order-driven, which means that production or transportation is triggered by requests sent from nodes to their predecessors within the network (Almeder et al., 2009). Material flow processes in the *Warehouse* class is controlled by the *Inventory* class. In addition, the warehouse object consists of the *Successor List* that indicates the respective downstream members connected to each of this node. Warehouse instances operate according to the following logic. Once a warehouse receives a request from a retailer, the quantity required is compared with the on-hand inventory to meet the retailer demand. If a warehouse has enough stock to supply the order, the order is shipped from the warehouse to its retailer and the installation's inventory level is updated by reducing the equivalent amount of the order from both on-hand inventory and inventory position levels.

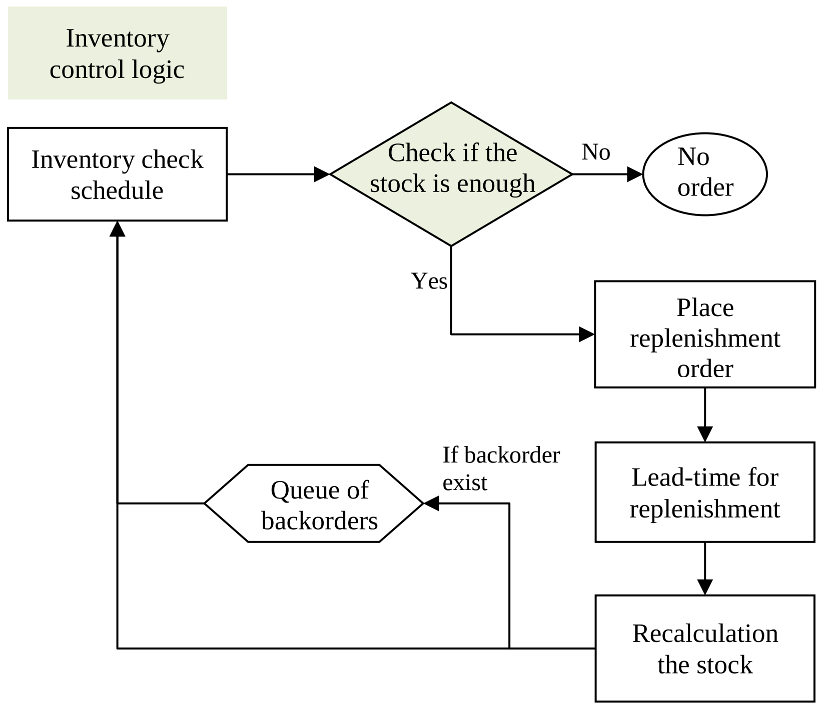


Figure 5-5: Flowchart of Process for Warehouse Inventory Control

However, if there is not enough stock to supply the order, the unsatisfied demand becomes backlogged. It will only be satisfied once the warehouse receives adequate replenishment from the upper echelon. Backordered quantities are recorded to calculate the warehouse performance measures, such as fill rate. Figure 5-4 shows the supply operation flow chart of warehouse class. For each warehouse class object, a process is defined to review inventory position continuously or periodically depending upon the inventory control policy. Whenever the inventory level is less than the reorder point for the product, a predefined order is placed. This process is illustrated in Figure 5-5. Once the simulation has reached the maximum simulation period, the total cost of the warehouse is calculated using inventory holding cost, backorder cost, and ordering cost as well as the customer service level.

5.3.7 The **Inventory** *Class*

The Inventory class provides methods for requesting inventory and for filling demands (Rossetti et al., 2006). Every *Inventory* class is associated with an inventory policy that allows the description of rules to manage the material flow in the stock. *Inventory* class has several important methods, such as *StockGeneration(), CheckInventory(),* and *UpdateInventory()*. The *StockGeneration()* method updates the on-hand inventory level of the stock point, reduces it by the amount of filled demand, and updates the backordered item list. Orders are created with the inventory evaluation event using the *CheckInventory()* method. The method checks the current inventory level and places an order when it is necessary. The order receiving process is controlled by the *UpdateInventory()* method. Whenever orders that were placed at some point in the past arrive, the inventory information of the node is updated using this method.

5.4 The Simulation Model Cost Structure

In this section, a cost structure of the multi-echelon inventory system is developed. In a distribution chain, there are mainly two types of costs: inventory cost at each node and transportation cost between different nodes. The sum of logistic costs for all nodes in a network is expressed as (Güller et al., 2015):

$$TSC = TSCH + TSCB + TSCO + TSCT$$

where *TSCH* is the total holding cost, *TSCO* is the total order cost, *TSCB* is the total backorder cost and *TSCT* is the total transportation cost. Next, each part of the cost is explained in detail.

5.4.1 Inventory Cost Structure

Each *StockPoint* object of a simulation model has its own inventory cost parameters. Inventory cost at a stock point comprises two types of costs: fixed cost for placing an order and variable cost for carrying the inventory. Storage of products leads to inventory cost, which incorporates cost functions depending on the stock levels. Inventory on hand and backorder, respectively, at a location *i* at the end of period *t* is given by:

$$OnHand\ at\ time\ t = I_t^{i+} = \left(I_{t-1}^i + Q_t^i - D_t^i\right)^+ \quad 5\text{-}1$$

$$Backorder\ at\ time\ t = I_t^{i-} = \left(I_{t-1}^i + Q_t^i - D_t^i\right)^- \quad 5\text{-}2$$

The inventory cost including holding cost, shortage cost, and order cost can be expressed as:

$$InvCost(t) = CarryingCost(t) + OrderingCost(t) \quad 5\text{-}3$$

$$CarryingCost(t) = \begin{cases} h \times (t - t_p) \times I_t & if\ I_t \geq 0 \\ p \times (t - t_p) \times I_t & if\ I_t < 0 \end{cases} \quad 5\text{-}4$$

$$OrderingCost(t) = d \times A \quad 5\text{-}5$$

Where: h is holding cost per unit item per unit time

p is shortage cost per unit item per unit time

A is fixed ordering cost

t is present time

t_p is time for previous demand

I_t is net inventory which equals to on hand inventory minus backordered demands.

$$\begin{cases} d = 1\ if\ an\ item\ is\ ordered\ by\ object\ in\ specified\ time \\ d = 0\ else \end{cases}$$

5.4.2 Activity-Based Cost Structure

The Activity-Based Costing approach is used to establish the actual expense for the order processing. The method involves breaking down activities into individual tasks or cost drivers, which help in estimating the cost. The cost drivers of an order fulfillment per item are order picking, order packing, consolidating and loading/unloading. Table 5-4 presents the activity-based cost components and related parameters.

Table 5-4: Activity- based Cost Parameters at DCs

Activity	**Cost**	**Description**
Order Preparing	1.20	$ per Order
Order Packing	0.05	$ per Carton
Unloading	0.30	$ per Pallet
Loading	0.20	$ per Pallet
Consolidating	0.10	$ per Carton

5.4.3 Transportation Cost Structure

Even though current research in logistic management highlight that the integration of production, inventory and transportation arising in a supplier–retailer logistic system has an increased importance, classical inventory management strategies usually have ignored transportation costs in the formulations or typically assumed that transportation cost is included in another cost such as setup cost (Mendoza & Ventura, 2011) (Zhao et al., 2004). Inventory models without taking into consideration quantity discounts are insufficient to analyze the impact of the shipment quantity on the per-shipment cost of transportation. Hence, inventory decisions made in supply chains, in which transportation cost, is neglected would fail to take advantage of the economies of scale (Güller et al., 2015). Moreover, the interrelationship between transportation cost, shipment sizes and transportation distance adds another dimension of complexity to incorporate the transportation cost into the inventory analysis. One of the fundamental issues of the incorporation of transportation costs into the analysis of order quantities is to assign the appropriate freight rate structure (Mendoza & Ventura, 2011).

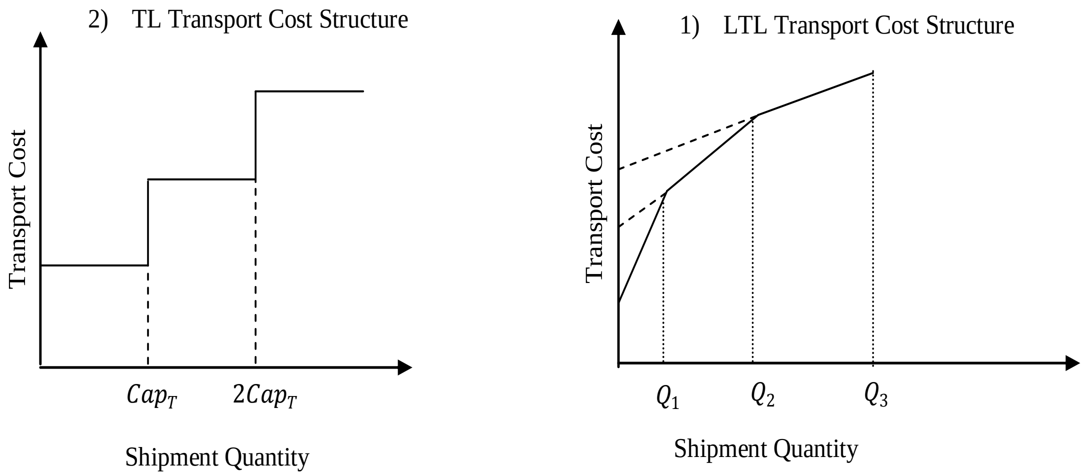


Figure 5-6: Two Transportation Cost Structures

Different structure of shipping freight cost are typically categorized as non-linear Less-than-truckload (LTL) transportation cost function and Full Truckload (FTL) transportation cost function (see Figure 5-6). The LTL cost function includes multiple breakpoints in the quantity shipped where the per unit cost decreases. In contrast to LTL, the FTL rate is independent of the quantity shipped as it has a fixed cost that is incurred for each load up to a given capacity (Riksts & Ventura, 2010). If shipment quantities between supply chain members are relatively small and less than the vehicle capacity, multiple incremental quantity discounts are applied to the additional shipment quantities beyond the predetermined breakpoint (Xin, 2007). In this situation, decision-makers face a basic tradeoff: make smaller shipments from the supplier more frequently at a higher per-unit shipping cost, or make larger shipments less frequently, which increases the holding cost at the warehouses. Therefore, the objective of integrated inventory management is to find an optimal shipment quantity that includes the quantity discount effect and, at the same time, to control the inventory cost at the stock point.

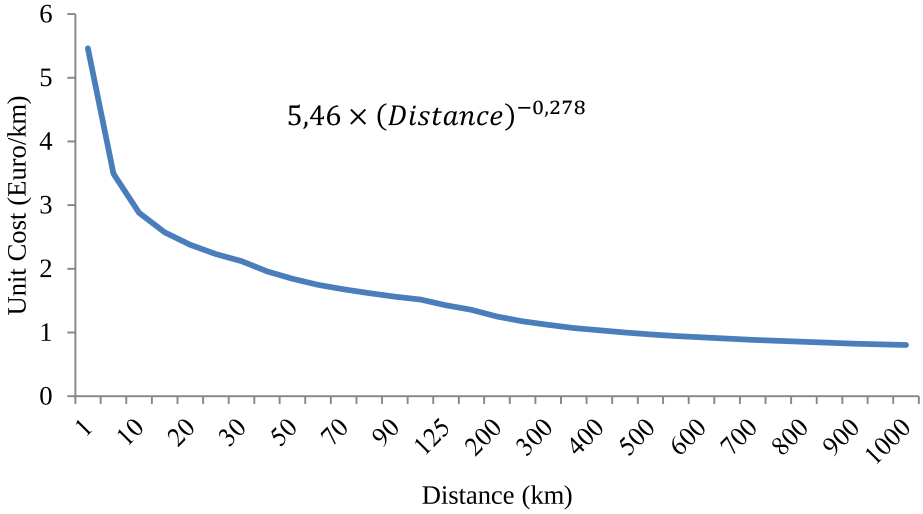


Figure 5-7: Distance-dependent Unit cost function (Janic, 2007)

It is common knowledge that shipping costs are typically a function of the distance and the size of the shipment. The transportation cost per unit can be estimated in two ways. The first way is to determine the shipping cost per unit as a rational function. The second way is to generate rates over a realistic range of shipment quantities (Q) for a lane and then fit a curve having some functional form (Tyworth & Ruiz-Torres, 2000). This approach is effective when trucking companies offer discounts on the freight rate to encourage shippers to buy in large quantities. Tywort and Ruiz-Torres (2000) proposed the use of power function to model LTL freight rates as follow:

$$F_{LTL}(Q) = \alpha(Qw)^{\beta} \tag{5-6}$$

where α and β are the corresponding coefficients. These coefficients can be found using nonlinear regression analysis. In this research, the distance-dependent cost for trucks based on the full vehicle load is assumed to be $5{,}46 \times (Distance)^{-0{,}278}$ vehicle-km (Janic, 2007)(Figure 5-7). The LTL transportation cost rates offered by the transportation third party for four major distances, which are approximately 100, 250, 500 and 1,000 km in length, is illustrated in Figure 5-8 (Aldarrat, 2007). The estimated full truck load cost for the 100, 250, 500 and 1,000 km are, respectively, as follow: 150, 300, 485 and 800.

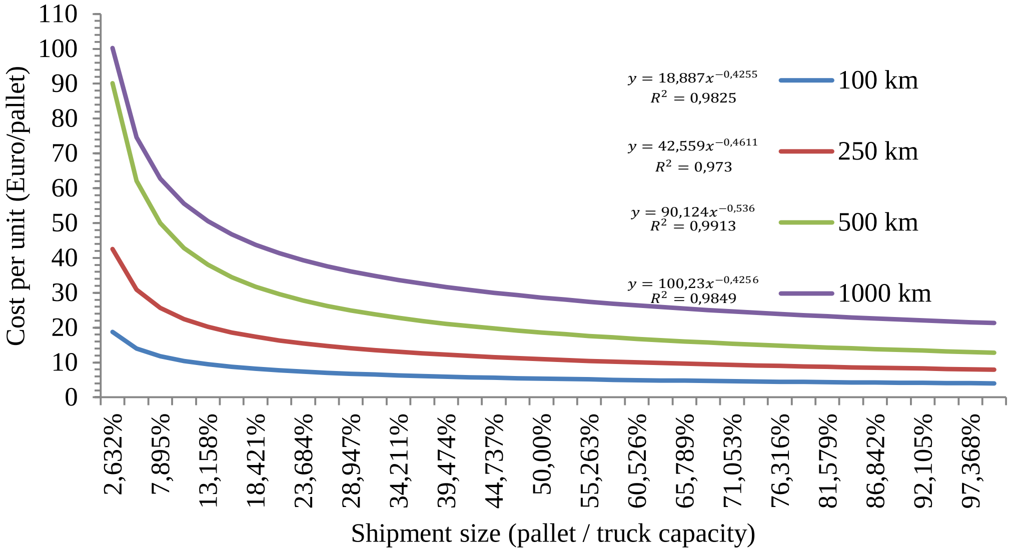


Figure 5-8: Examples of Freight Rates (Distance-Shipment Based) (Güller et al., 2015)

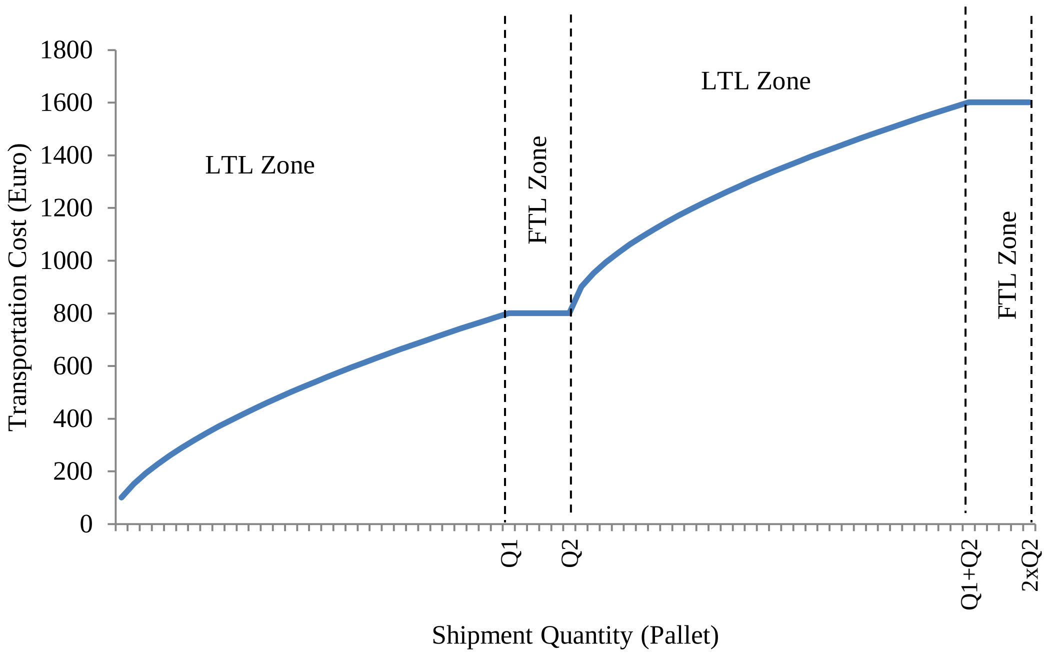


Figure 5-9: A dual-mode transportation cost structure for 1000 km distance (Güller et al., 2015)

In order to contribute to incorporation transportation costs into inventory replenishment decisions, a dual mode transportation cost structure including full truckloads and a less than full truckload carrier is used as illustrated in Figure 5-9. The two-mode transportation cost structure can be interpreted as follows (Xin, 2007): For a quantity smaller than Q_1, the LTL transportation cost is adopted. If the shipment quantity falls between $Q_1$and Q_2, it is optimal to choose FTL transportation mode. As a consequence, the transportation cost is a constant value independent of the shipment quantity. Once the first truck is fully loaded, the warehouse chooses a combination of the two transportation modes by shipping the excess quantity in LTL transportation mode.

5.5 Supply Chain Performance Measures

It is important to define appropriate performance measures in logistic network design and analysis. A performance measure, or a set of performance measures, describes the feedback information to determine the efficiency and/or effectiveness of an existing system, or to compare alternative systems (Beoman, 1998). According to Beamon (1999), performance measures can be categorized as qualitative and quantitative. Qualitative performance measures are the measures that cannot be directly described numerically, such as customer satisfaction, flexibility, and supplier performance. Quantitative performance measures can be presented in numerical format. Quantitative supply chain performance measures may be associated with the objectives of the supply chain: cost, profit, and customer responsiveness. In this research, the performance measures identified through simulation are total system-wide cost, average waiting time in the system, average number of backorders and customer responsiveness.

5.5.1 Notations

In this section, the notations used in the multi-echelon inventory system are introduced as follows:

Table 5-5: Notation explanation for the simulation model

Variables	**Definition**
index	
j	Plants index
k	Warehouse index
l	Distribution center index
t	Time index
parameters	
J	Number of plants
K	Number of warehouses
L	Number of distribution center
I_t^i	Average inventory level of location *i* at time *t*
B_t^k	Average backordered items of location *i* at time *t*
T	Planning period
O_t^i	Number of placed order by location *i* at period *t*
h_i	Holding cost per item per time at location *i*

p_i	Stockout cost per item per time at location *i*
A^i	Fixed order cost at location *i*
TR_c	Truck Capacity
Q_i	Replenishment quantity of location *i* in pallet unit
$F_{kj}()$	Transportation cost function between location *k* and *j*
D_t^i	Total demand in location *i*'s customer zone during a period *t*
W_t	Waiting time
L_t	Lead-time
R_t	Replenishment time
P_t	Order placed time
OPK^i	Number of order-picking cartons at location *i*
$OPKC^i$	Order-picking cost per carton at location *i*
$LoadC^i$	Loading cost at location *i*
$ULoadC^i$	Unloading cost at location *i*
$PackC^i$	Packing cost at location *i*

5.5.2 Measure Based on Cost

The total cost function consists of five costs: holding cost, backorder cost, ordering cost, warehousing cost and shipping cost. The holding and backorder costs are composed of costs due to warehouses' inventory and retailers' inventory. Supply chain costs in this model consist of the following components:

- Total Supply Chain Holding cost of products at all stock points.

$$AverageInventory = I_{All,t} = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} I_t^i}{T} + \frac{\sum_{l=1}^{L}\sum_{t=1}^{T} I_t^l}{T} \quad 5\text{-}7$$

$$TSCH = \sum_{t=1}^{T}\sum_{k=1}^{K}(I_t^k \times h_k) + \sum_{t=1}^{T}\sum_{l=1}^{L}(I_t^l \times h_l) \quad 5\text{-}8$$

- Total Supply Chain Stock-out cost of products.

$$AverageBackorder = B_{All,t} = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} B_t^k}{T} + \frac{\sum_{l=1}^{L}\sum_{t=1}^{T} B_t^l}{T} \quad 5\text{-}9$$

$$TSCB = \sum_{t=1}^{T}\sum_{k=1}^{K}\left(B_t^k \times p_k\right) + \sum_{t=1}^{T}\sum_{l=1}^{L}(B_t^l \times p_l) \quad 5\text{-}10$$

- Total Supply Chain Ordering Cost (TSCO)

$$TSCO = \sum_{k=1}^{K}\sum_{t=1}^{T} O_t^k \times A^k + \sum_{l=1}^{L}\sum_{t=1}^{T} O_t^l \times A^l \quad 5\text{-}11$$

- Total Supply Chain Warehousing Cost = Loading + Unloading + Packing + Order Picking Costs

$$TSCW = \sum_{k=1}^{K}\sum_{l=1}^{L} OPK^{kl} \times OPKC^{kl} + \sum_{l=1}^{L}\sum_{k=1}^{K} Q_{kl} \times LoadC^{kl} + \sum_{l=1}^{L}\sum_{k=1}^{K} Q_{kl} \times ULoadC^{kl} + \sum_{l=1}^{L}\sum_{k=1}^{K} OPK^{kl} \times PackC^{kl} \quad \text{5-12}$$

- Total Supply Chain Transportation cost of product shipped from Manufacturing Plants/Manufacturer's Warehouses to Distribution Center and from Distribution Centers to Retailers

$$TSCT = \sum_{k=1}^{K}\sum_{i=1}^{J}\sum_{t=1}^{T} F_{kj}(Q_{kj}) \times Q_{kj} + \sum_{l=1}^{L}\sum_{k=1}^{K}\sum_{t=1}^{T} F_{lk}(Q_{lk}) \times Q_{lk} \quad \text{5-13}$$

Now the expected total cost function of the multi-echelon supply chain is the sum of the warehouse's and the retailer's total cost equations given in Equations 5-7 and 5-13. In summary, the total integrated cost can be computed by adding up the cost components previously described and dividing by planning horizon as follows:

$$TSC = \frac{TSCH + TSCB + TSCO + TSCW + TSCT}{T_{days}} \quad \text{5-14}$$

5.5.3 Measure Based on Customer Service Level

To measure customer satisfaction or the ability to effectively respond to customer demand, service levels are commonly used as a key performance indicator by an organization. The most common measures of service are (1) α service level, (2) β service level, and (3) γ service level (Silver et al., 1998), (Diks et al., 1996). The first type of service level is also called the cycle service level. It measures the probability that the net stock is non-negative at the end of an arbitrary period. The β service level, or fill rate, is a quantitative measure that represents the fraction of customer orders that is filled by on-hand inventory. The γ service level is one minus the ratio of the average backorder at a stock point immediately before arrival of a replenishment order to the average demand during an arbitrary replenishment cycle.

$$\beta_i = \left(\frac{1}{L}\sum_{i}^{L}\beta_i + \frac{1}{K}\sum_{i}^{K}\beta_i\right)/2 \qquad \text{5-15}$$

$$= \left(\frac{1}{L}\left(\sum_{i}^{L}(1 - \frac{\text{total number of backorders}}{\text{total number of orders}})\right)\right.$$

$$\left. + \frac{1}{K}\left(\sum_{i}^{K}(1 - \frac{\text{total number of backorders}}{\text{total number of orders}})\right)\right)/2$$

$$= \left(\frac{1}{L}\sum_{i}^{L}\left(1 - \frac{\sum_{t=1}^{T} B_i^t}{\sum_{t=1}^{T} D_i^t}\right) + \frac{1}{K}\sum_{i}^{K}\left(1 - \frac{\sum_{t=1}^{T} B_i^t}{\sum_{t=1}^{T} D_i^t}\right)\right)/2$$

5.5.4 Measure based on Order Response Time

A node of a supply chain has five basic actions with regard to the life cycle of an order which may be performed differently depending on the type of node: order creation, order placement, order processing, order shipping, and order receiving (Chatfield et al., 2006). The length of time between the placement of an order and its receipt is called replenishment leadtime. Note that the replenishment leadtime is potentially variable and depends on the availability of on-hand inventory at the upstream supplier (Kaboli, 2013). In the event the central warehouse is out of stock, the DC waits an additional time, W_t, the time until the warehouse is replenished by one of its suppliers. Therefore, the total replenishment time of the distribution center, R_t, is:

$$R_t = L_t + W_t \qquad \text{5-16}$$

In Equation 5.16, L_t is the transportation between the central warehouse and the DC. Again, even if the transportation time is deterministic, the waiting time is a random variable and therefore so is the actual lead time. The random variable lead-time demand is the key to determine the optimal inventory strategy (Zipkin, 2000). Since order response time is a time-based measure, it is also a key indicator of performance. Consequently, a service level measure based on response time for an order can be defined as the total number of products delivered on time:

$$ResTime_i = \frac{\sum_{n=1}^{N}(R_t^n - P_t^n)}{N} \qquad \text{5-17}$$

5.6 Summary

In this chapter, a special library is described for the inventory simulation of multi-echelon supply chain by using the object-oriented modeling approach (i.e., library using Microsoft Visual C-Sharp), in which any part of the system with a set of classes is presented. These classes include operations and objects representing nodes, interactions between nodes, and the management of moving material between the different nodes within the network. To define the performance measure of the supply chain, a cost structure and other indicators are introduced. The total cost function consists of five costs: holding cost, backorder cost, ordering cost, warehousing cost and transportation cost. For the transportation cost, two types of freight rate structures are presented: a non-linear Less-than-truckload (LTL) transportation cost function and a Full Truckload (FTL) transportation cost function.

Chapter 6

Multi-echelon Supply Chain Inventory Simulation Tool

This chapter addresses the development of a graphical user interface that depicts the planning, managing and controlling of an inventory system; provides a brief description of input and output parameters of the simulation model; outlines the assumptions made during the simulation; and displays a pilot simulation environment for analyzing the behavior of different inventory control strategies. As an application example of developed object-oriented simulation framework a case study from the logistics domain is briefly introduced. The main purpose for the experiments and case study in this section is to show the effectiveness of the simulation model. By means of this simulation framework economic implications of alternative replenishment and queue strategies are analyzed and evaluated. The simulation experiment consists of the basic supply chain nodes, each of which has its own customers, suppliers, and inventory policy. The benefits of the tool are its capability to link with databases to import and export information, graphical user interface, and integration of the optimization tool. This tool provides broad functionality for optimization and analysis of output files. The rest of this chapter is organized as follows. Section 6.1 presents the simulation environment. Section 6.2 introduces the supply chain simulation case study and the experimental settings. The simulation study with numerical results is the subject of Section 6.3.

6.1 Simulation Environment

6.1.1 Simulation Tool Input Parameters

Several input parameters are required to run the simulation model correctly. In particular, data on plants, central warehouses, DCs, retailers, and the transportation specification are necessary. The simulation model is linked to MS Excel, MS Access and SQL Database where all parameters are entered, and then imported to the model at the start of the simulation. To implement the simulation model, the major inputs divided in five groups are described below:

Geographical Parameters:

- Customer or Market Area: Site name, city, zip code, location,
- Plants, Warehouses, and Distribution Centers: Site name, city, zip code, location,
- Design Parameters: Number of stages, number of facilities per stages, network type (convergent, divergent, serial, etc.).

Network Policies and Strategies:

- Inventory Policy: Determine inventory control policy (continuous or periodic) and inventory control parameters (order quantity, reorder point, safety stock, etc.),
- Replenishment Strategy: Determine the replenishment order size (EOQ, Optimized) and inventory concept (installation or echelon concept),
- Transportation Strategy: Determine transportation strategy, such as Less than Truck Load (LTL), Full Truck Load (FTL), or dual-mode transportation in which products can be shipped in two transportation modes.

Cost Parameters:

- Inventory Cost: In order to evaluate the cost of the proposed strategies, the following cost parameters need be inputted: a holding cost per unit per period, a backlog cost per unit time, order-processing cost, and activity-based cost parameters.
- Transportation cost for possible transportation mode and freight rate costs.

Operational Parameters:

- Transportation times between the central warehouse and the distributors, the leadtime between the distributor and its customers.
- Daily demands per customers, demand variances, and fitted distribution,
- Production rate at factory,
- Target fill rate for each installation.

6.1.2 Simulation Tool Outputs

The simulation tool provides the ability to compare output from various scenarios both graphically and textually. In order to compare the different strategies and to measure the results of simulation, numerous performance metrics are generated and analyzed during the simulation. The summary file contains performance characteristics over all replications for each supply chain member and the whole system. Moreover, a detailed report and results are typically written to text files and exported to an Excel sheet after a simulation run. By clicking the corresponding "*Simulation Result*" button in the simulation tool, statistics associated with supply chain performance are displayed on the screen such as shown in Figure 6-1 and Figure 6-2.

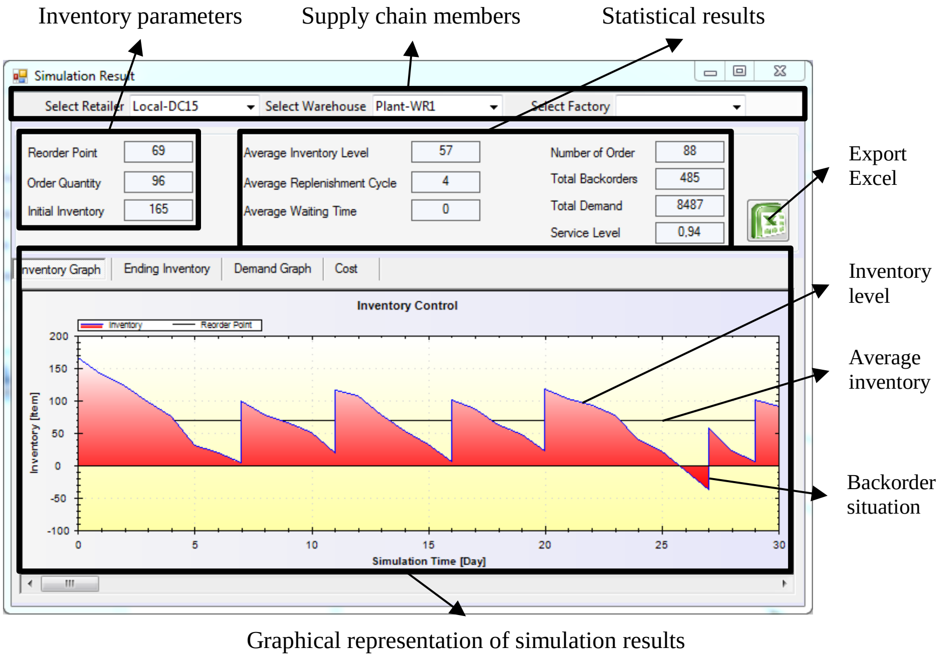
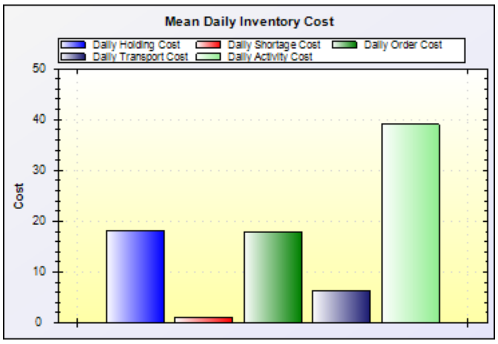


Figure 6-1: Inventory Simulation Output Screen

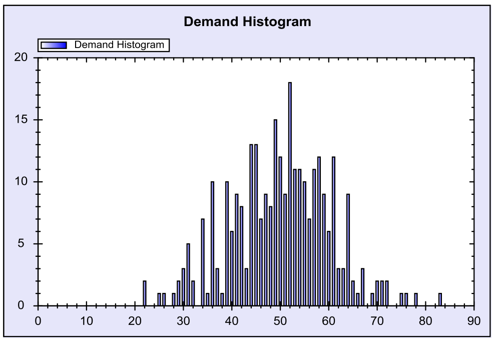
One of the key output statistics for analysis is the inventory and backorder level chart. It shows the on-hand inventory, the backorder level, the reorder point, and the safety stock. Furthermore, graphically, demand per period of each node in a supply chain can be viewed as histograms and plots (see Figure 6-2). The free graphing library called ZedGraph is used to generate graphs. ZedGraph is an open source library written in C# for creating 2D line graphs, various curves and bar graphs based on arbitrary datasets (ZedGraph, 2009). In addition to total system-wide cost, some other important results designed for detailed analysis of each node include the following information:

- Costs incurred at each of the nodes (holding cost, shortage cost, order cost, activity-based cost and transportation cost),
- Average inventory on hand and average backorder level,
- Average replenishment cycle times,
- Order lead times,
- Average waiting time for orders,
- Service levels and other related information,

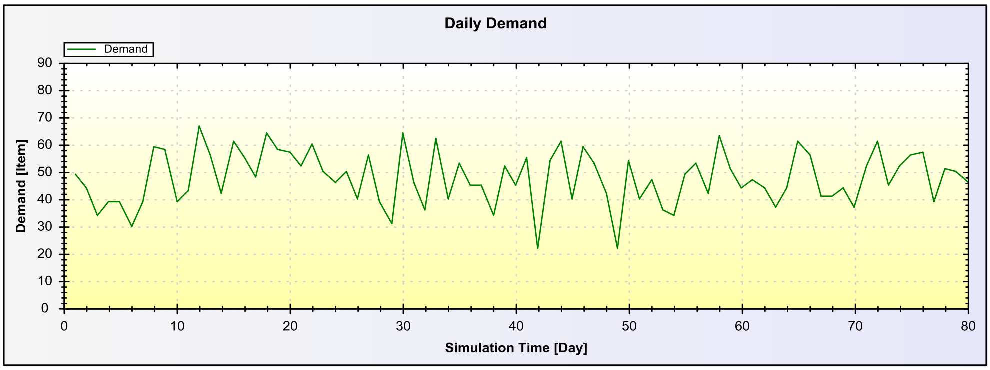
- Number of orders placed on the upstream stage for the selected period.



a) Total Cost



b) Demand Histogram



c) Daily Demand

Figure 6-2: Example simulation graph outputs

6.2 Illustrative Example and Simulation Settings

In this section, a case study is conducted with the proposed simulation model. The modeling methodology is applied to the supply chain of a major food product company in Europe. A make-to-stock (MTS) supply chain network with manufacturers, finished goods warehouses, regional distribution centers with planned inventories and retailers were all considered. The given network consists of 3 manufacturing sites, 3 plant warehouses, 19 regional distribution centers, and approximately more than 1,000 retailers spread over the country. From the plants' warehouses the goods are shipped to the regional distribution centers from which they are delivered to the retail stores (Güller et al., 2015). Figure 6-3 illustrates the network considered under the study. Under the given supply chain network, products at plants are produced according to a constant production rate that is larger than the DC's demand rate ($P > D$ where $D = \sum D_l$). In other words, items are produced in batches at a finite rate at plants. The plants do not produce the same product types. Historical sales data reveals that the DCs' demand is split between the plant warehouses as follows: 62% of the demanded products supplied by plant-3; 28% of the products supplied by plant-1; and 12 % of the products supplied by plant-2.

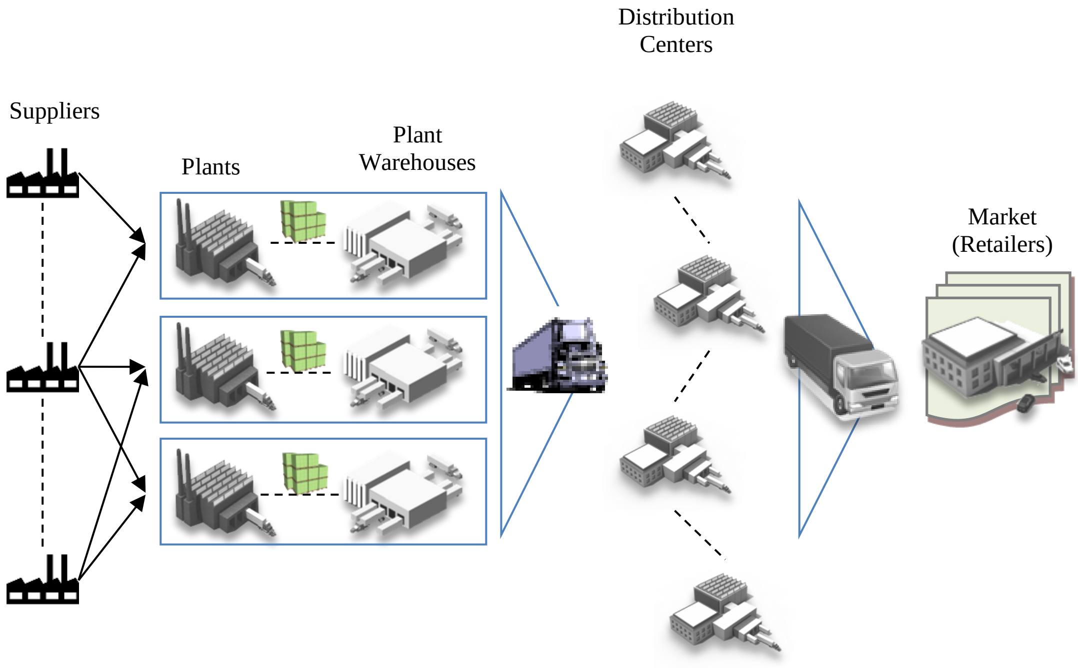


Figure 6-3: Given structure of the distribution network

One of the main difficulties encountered in MTS is to define the remanufacturing point in inventory, where the production decision for an item at a plant is initiated. According to Figure 6-4, plants produce the final products with the production lot size Q_0 where the lot size is a decision variable.

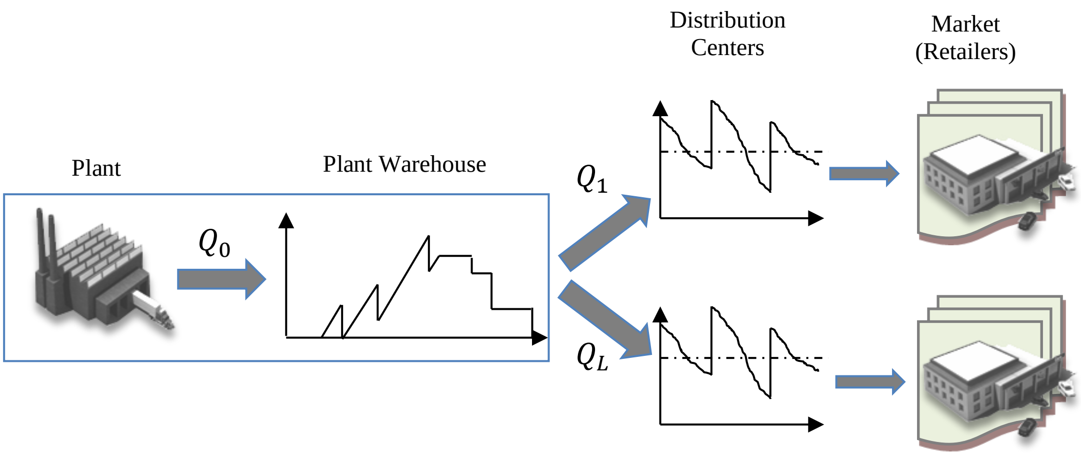


Figure 6-4: Two echelon production-inventory system

After the production process at plant, the products appear in its finished goods inventory and customer orders are typically filled from this existing stock. Continuous review system is considered at DCs, in which order quantity $Q_l$and reorder point R_l are main decision variables. In this context, whenever the inventory level in DCs drops below the reorder point R_l, it triggers an order Q_l. It is assumed that the replenishment orders are always placed at the end of the day and each distribution center receives daily orders of items from retailers. Any customer order that cannot be filled immediately is backordered.

Data collection is a critical supply chain activity to quantify the associated system variables (De Sensi et al., 2008). The Data Collection step takes care of collecting data in each member of the supply chain as well as finding the most suitable input parameter for the simulation model. Each distribution center receives daily orders of different items from retailers and customers. The average daily demand for each item is fitted to some theoretical probability distributions using historical sales data of DCs.

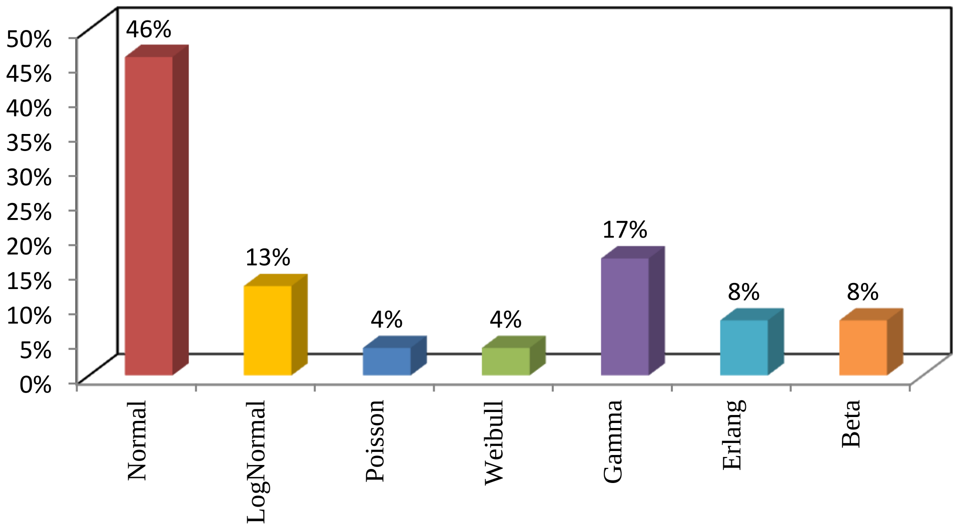


Figure 6-5: Percentage of each Probability Distribution of Demand for a Warehouse (Housein, 2007)

A large number of studies assume a homogeneous normal distribution demand pattern in supply chain problems because of its convenient mathematical properties. However, actual customer demand may be better modelled with distributions that are asymmetric and positive skew shape (Cobb et al., 2013). According to Tyworth and O’Neill (1997), the normal approximation can lead to significant errors in safety stock. Figure 6-5 presents the percentage of fitted probability distribution of a domestic product for DCs. As shown in Figure 6-5, items are not homogeneous in terms of demand distribution. Figure 6-6 shows the aggregated daily average demand, the standard deviation, and the coefficient of variation (CV). Appendix C presents the fitted probability distribution for each distribution center in the considered supply chain.

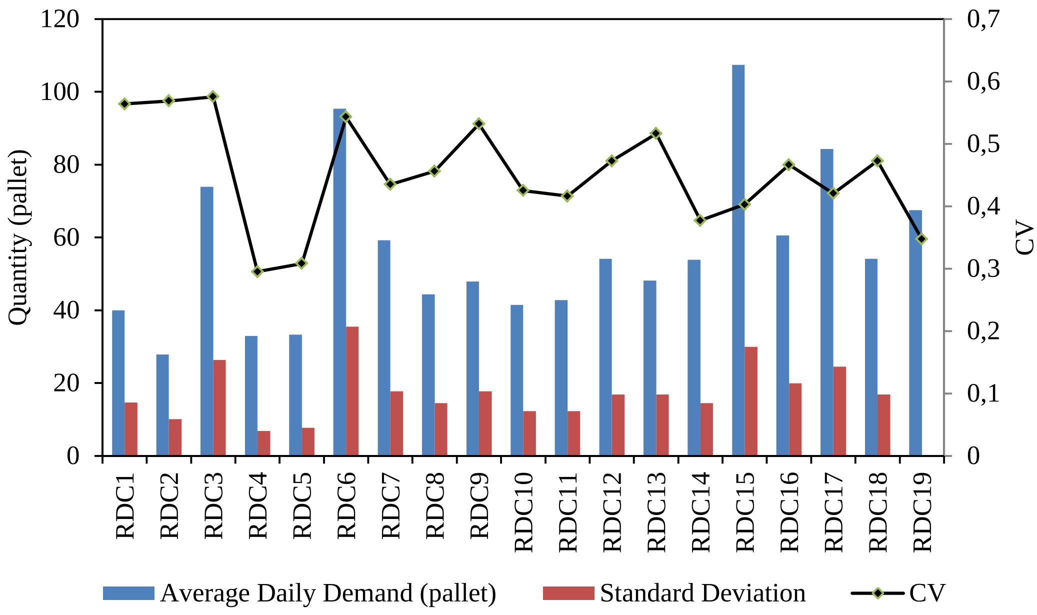


Figure 6-6: Aggregated Average Daily Demand of DCs

6.2.1 Simulation Model Assumptions

Other assumptions made in the simulation study are listed briefly as follows:

- Production rate P at plants is fixed and is larger than the DC's demand rate ($P > D$ where $D = \sum D_i$).
- Continuous review inventory policy (R, Q) is used at each node of the supply chain and inventory is reviewed every day.
- The initial inventory level of the stock points are assumed $(R + Q)$ to prevent the initial inventory status from being unrealistically "empty and idle" (Chen & Li, 2009).
- All unfilled orders are backordered, not lost sales, and delivered based on FIFO, LIFO or priority-based policy when adequate inventory is available.
- High-capacity trucks, each of which has a loading capacity of 38 pallets, are used to move the full pallet product from the plant warehouses to regional distribution centers with Standard European Pallets with a height of 2.4 m height.
- Due to the palletized shipment constraint, some parameters of the system must be converted to units of pallets. The replenished quantity for a stock point i (Q_i) rounded up to make a full pallet per item type. The minimum quantity is one pallet.

6.2.2 Simulation Scenarios

The simulation model previously described is used to simulate different scenarios and strategies. Several experiments are conducted to analyze the responses total inventory cost and service level. The changing factors are inventory control parameters, capacity ratio, and queue policy for distribution centers' orders. In simulation scenarios, a traditional model (referred to as decentralized decision making-process) is considered, in which information is not exchanged among supply chain members. In other words, in a decentralized system, the inventories at each installations of the supply chain are controlled independently based on local information. As described in the previous section, a Make-to-Stock (MTS) production-inventory system with backorders under the continuous-review (Q, R) policy is considered. In MTS strategy, the manufacturer has to decide when and how many items to produce to stock. Several strategies for the reorder point to find effective inventory levels are proposed in the literature. Banerjee et. al. (1996) describe four installation reorder point policies with no information sharing.

- RSTD (Expt-Set-1): An order is triggered when the inventory position declines to a reorder point calculated for a given desired service level.

$$R_k = \left(\sum_{i=1}^{L} D_i\right) \times L_k + k_k \times \sigma_k \times \sqrt{L_k} \qquad 6\text{-}1$$

- RAVGQ (Expt-Set-2): An order is sent to a supplier when the inventory position declines to the average demand lot size from the downstream echelon.

$$R_k = \frac{\sum_{i=1}^{L} Q_i}{L} \qquad 6\text{-}2$$

- RQMAX (Expt-Set-3): An order is sent to a supplier when the warehouse inventory position declines to the maximum demand lot size of the downstream echelon.

$$R_k = Maximum\{Q_l\} \qquad 6\text{-}3$$

- RHSUMQ (Expt-Set-4): An order is sent to a supplier when the warehouse inventory position declines to half the sum of all demand lot sizes from the downstream echelon.

$$R_k = \frac{1}{2}\sum_{i=1}^{L} Q_i \qquad 6\text{-}4$$

Many inventory settings discussed in the literature assume that all customers have the same standards of service and, thus, customers are served based on a first-come, first-served basis (FCFS). In practice, however, there are cases with multiple demand classes having different service and price. With an advanced strategy, the warehouse can separate its downstream customers into multiple classes according to priority levels and manage the inventory appropriately as shown in Figure 6-7. Iyer (2001) developed a queue model in which a non-preemptive priority (PR) is provided to orders from retailer locations with higher demand uncertainty. Under PR policy, the high priority customers will face a lead time with a smaller mean and variance, and the lower priority locations will face a lead time with a higher mean and variance as compared to FCFS. Rossetti and Xiang (2010) consider the backlog queue using a priority mechanism based on the amount demanded. Demands with fewer units demanded are placed at the front of the queue.

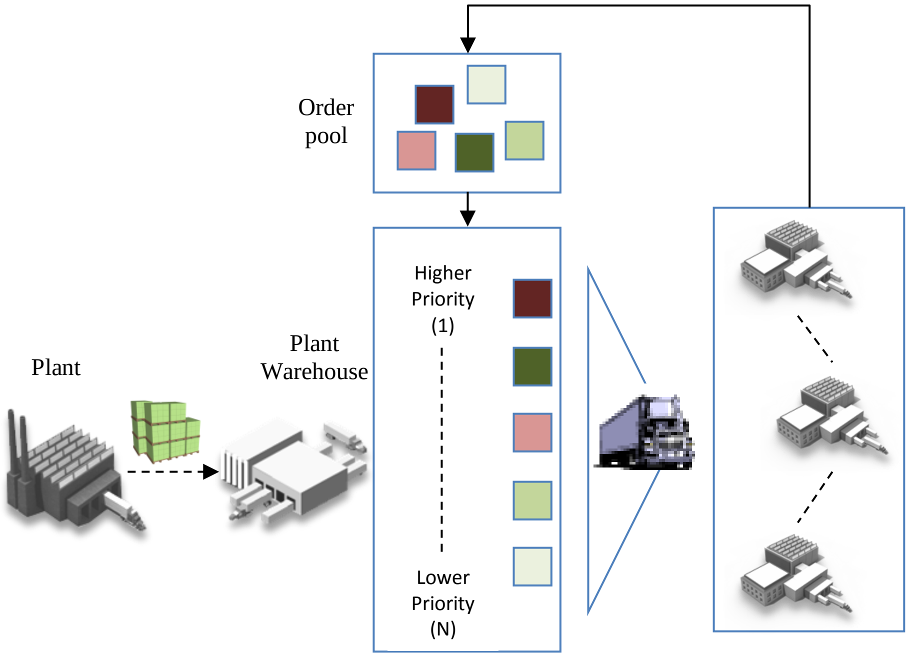


Figure 6-7: Multiple Demand Classes Inventory System

Literature shows dividing the customers into different priority groups to be served increases companies' performance and saves customers within the high-priority class time, which may increase their satisfaction. The challenge in this study is to analyze the impact of customer differentiation and multiple demand classes on the system performance in a multi-echelon production-inventory system. Order fulfillment rules become more important when the upstream location does not have enough inventories to satisfy all orders. As implied by the descending order of the priority parameter, the downstream customers are prioritized with class 1 having the highest priority, and class N having the lowest priority. The comparison between different rules is provided by simulation. The priority scenarios under consideration are:

- Scenario-1 (FCFS-Policy): When a customer order for a product is received from downstream locations, the order is placed in queue based on the first come, first served policy. Therefore, under this policy, completed items are allocated to the DC based on whose order has waited the longest time in the system.

- Scenario-2 (Priority-CV-Policy): To develop a multiple demand-class inventory model, customers are prioritized based on demand uncertainty. As implied by the descending order of demand uncertainty, we prioritize downstream customers with class 1 having the highest priority, and class N having the lowest priority.
- Scenario-3 (Priority-QMin-Policy): In this scenario the warehouse is assumed to meet the demands of its customers based on amount demanded. With this scheme the warehouse assigns a higher priority to its customer with lower batches demanded within a period.
- Scenario-4 (Priority-QMax-Policy): In this scenario the warehouse assigns a higher priority to its customer with highest batches within a period.
- Scenario-5 (Priority-QFreq-Policy): In this experiment, customers are prioritized based on order frequency.

6.3 Simulation Results and Analysis

In our experimental settings, each simulation run is replicated ten times. Simulation results are collected after running the model where the planning horizon is one year. It is out of the scope of this chapter to report all simulation results in detail. Some simulation results are reported and discussed at following sections. The base scenario is an experiment with the determination of the optimal safety stock setting given a 95% service level and order quantity calculated based on EOQ model (Appendix A). Figure 6-9 and Figure 6-8 indicate the results from the base experiment. The target service level is compared with simulated service level of each RDC in Figure 6-10. The figure clearly demonstrates the simulated service levels differ from the target service level. Each bar represents the interval expected fill rate to the simulated fill rate at RDCs. Values larger than zero indicate that the service level reached is higher than expected. On the other hand, values smaller than zero (with red color) means that the target service level is not reached.

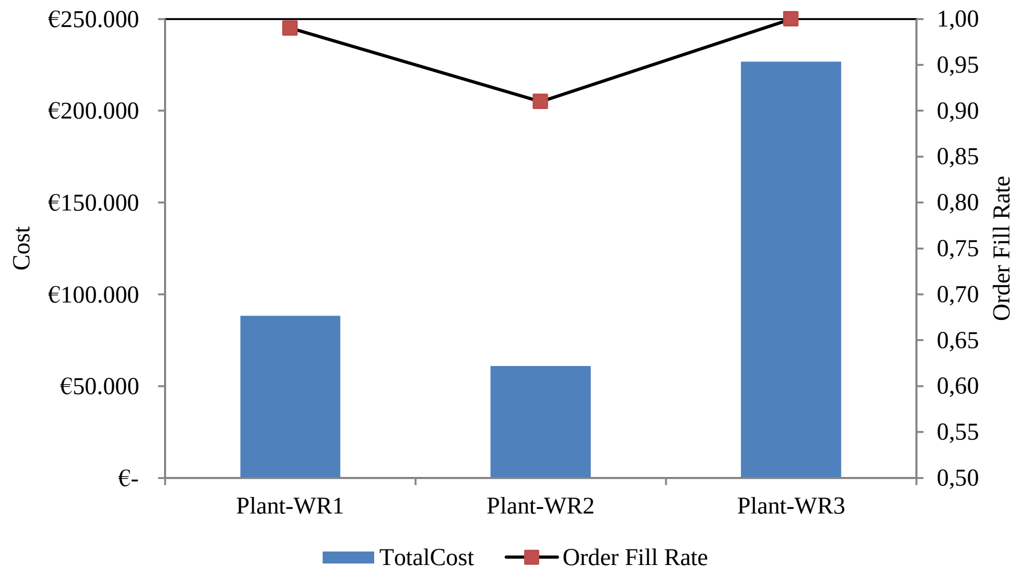


Figure 6-8: Simulated Total Supply Chain Costs of Plant-Warehouses for Base Experiment

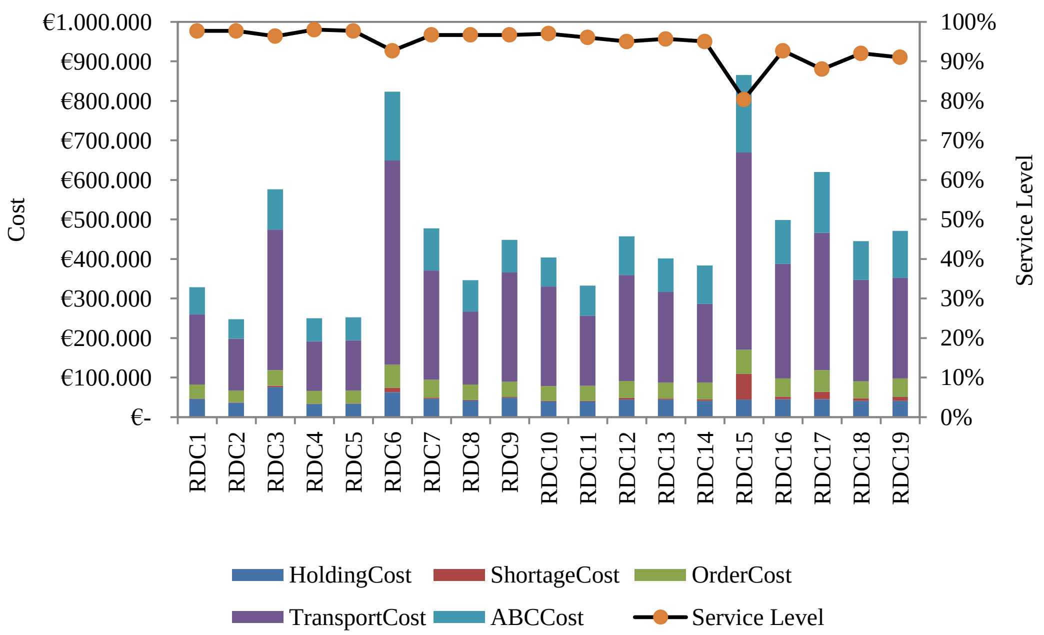


Figure 6-9: Simulated Total Supply Chain Costs of Each Local-DC

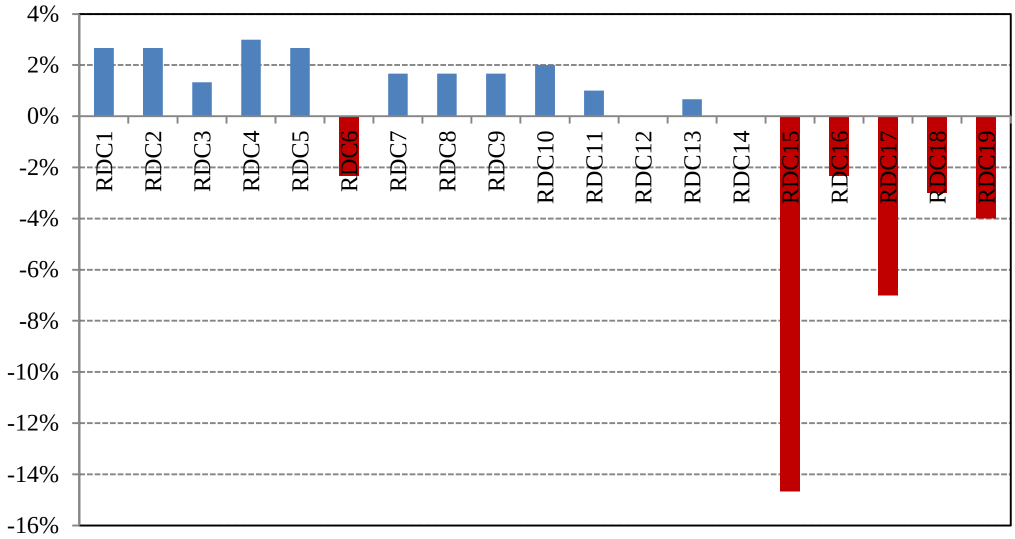
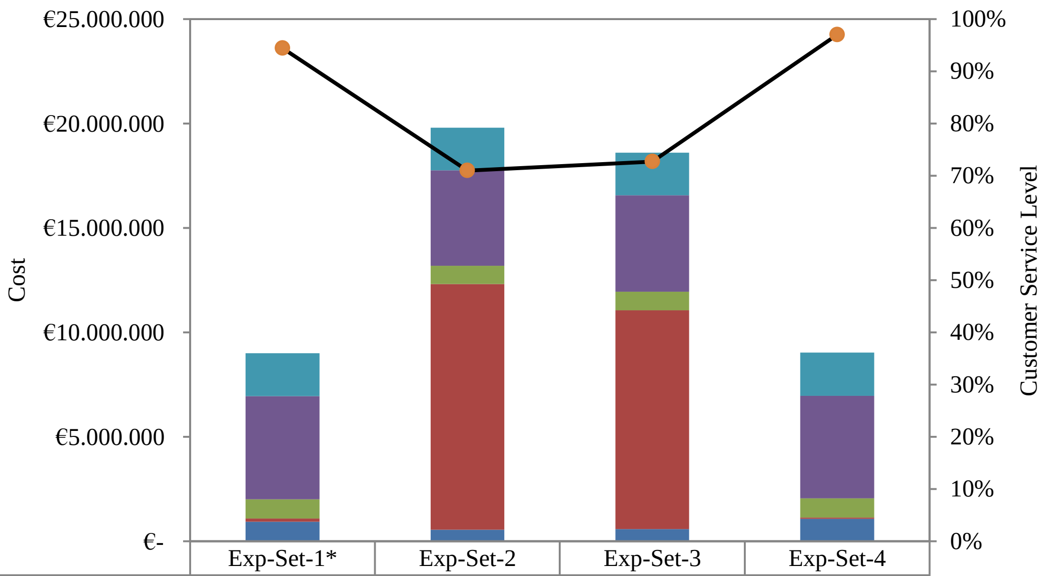


Figure 6-10: The Gap between Target Service Level and Simulated Service Level of DCs

6.3.1 Analysis of Replenishment Strategies without Information Sharing

The results of experimental sets are summarized in Table 6-1, where the numerical performance measures represent an arithmetic average of the ten replications. For continuous review policy without information sharing, we found that the best performance of the system is achieved with RHSUMQ policy. Although in this case the end-customer fill rate is better, the total system-wide cost is relatively small because of the lower stock-out level. The change in the relative fill rate performance of Exp-Set-4 compared to the base experiment seems to be significant as the change in the cost is relatively low. In Figure 6-11, it can be seen that, under RQMAX (Exp-Set-3) and RAVGQ (Exp-Set-2) strategies, the average customer service level at RDCs decreases while total cost dramatically increases as a result of stockout penalties.

In all the ordering policies without information sharing, there is a direct correlation between a warehouse's order fill rate and a DC's customer service level. Interestingly, some distribution centers perform very low in terms of service level in most of the experiments due to high variations in demand rate and stockout conditions at plant warehouses as shown in Figure 6-12 (for example RDC15). In other words, stockout level at Plant-WR has a significant impact on customer service level, depending on the order response time at the warehouse. In the event a warehouse goes out of stock, the regional-DCs wait an additional time. Since lead time of the DC's replenishment order is a function of the expected waiting time due to a lack of stock at the higher echelon, the backorder fraction increases at the lower echelon by increasing lead time uncertainty.



	Exp-Set-1*	Exp-Set-2	Exp-Set-3	Exp-Set-4
ActivityB.Cost	€2.043.333	€2.042.371	€2.050.596	€2.060.877
TransportCost	€4.939.929	€4.562.372	€4.615.980	€4.911.132
OrderCost	€923.680	€872.140	€880.600	€919.780
ShortageCost	€148.092	€11.752.984	€10.478.864	€54.611
HoldingCost	€945.652	€565.185	€581.244	€1.084.642
Service Level	94,400%	71,000%	72,700%	97,000%

Figure 6-11: Measures of performance for each uncoordinated strategy

Table 6-1: Simulation performance summary for replenishment policies

Experiment	Average Order Waiting Time	Order Fill Rate	Customer Service Level	Total Supply Chain Cost (€)
Exp-Set-1*	0,04	0,97	94,4%	9,000,686
Exp-Set-2	0,65	0,65	71,0%	19,795,051
Exp-Set-3	0,57	0,67	72,7%	18,607,284
Exp-Set-4	0,00	1	97,0%	9,031,041

*Base Experiment

Figure 6-12 illustrates that using FCFS strategy leads to unstable performance within the supply chain. This result confirms the extant literature on the First Come, First Served Rule ((Axsäter, 2007) and (Iyer, 2001)). Once multiple orders appear in the same day and the order amount exceeds the on-hand inventory of plant-warehouse, the distribution centers receive products based on FCFS strategy. However, FCFS leads to long waiting times for the orders at the back of the queue (see Figure 6-12).

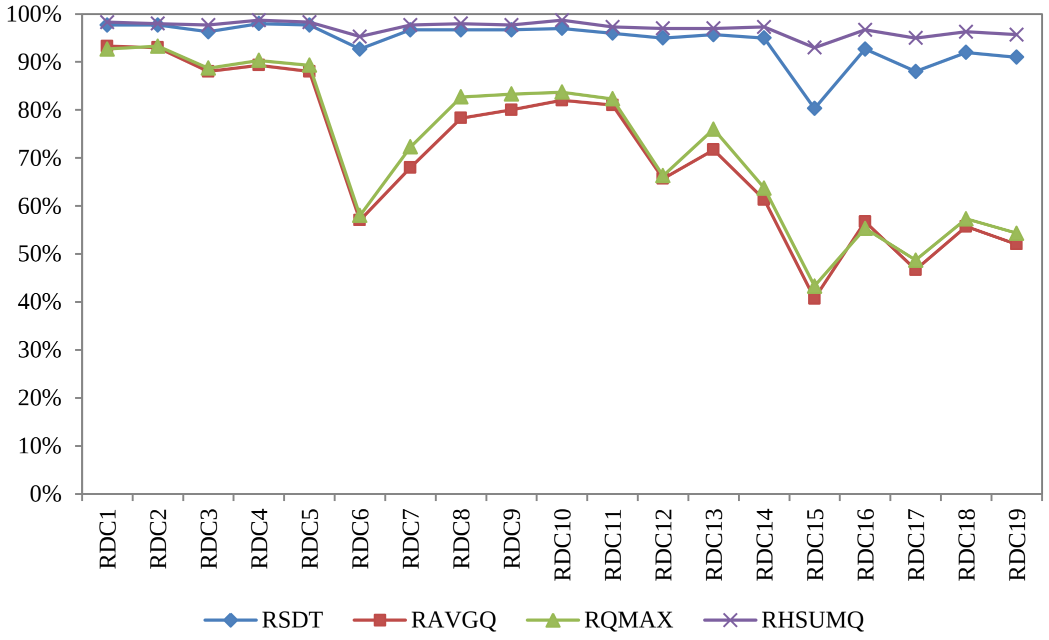


Figure 6-12: Customer service level of each distribution center with different replenishment policy

6.3.2 Analysis of Order Fulfillment Strategy

In this section, the impact of different order fulfillment strategies on system performance is discussed. To analyze the effects of customer prioritization in a better way, it is only considered experimental sets that have a low order fill rate such as Exp-Set-3. This assumption was made to understand the relationship between a random delay due to a stockout and the customer service level. With finite capacity, a plant that goes out of stock results in customers having to wait a long time. It also increases customers' risks from uncertain inventory availability.

Table 6-2: Cost Performance Measures of Exp-Set-1 under Different Queueing Policy

Priority	Holding Cost	Shortage Cost	Order Cost	Transport Cost	Activity Cost	Total Cost (€)
FCFS	11%	2%	10%	55%	23%	9,000,686
CV	11%	2%	10%	55%	23%	9,010,048
QMin	10%	4%	10%	53%	22%	9,133,102
QFreq	10%	5%	10%	53%	22%	9,337,786
QMax	11%	1%	10%	55%	23%	8,975,906

The comparison between the performances of the FCFS, PRIORITY-CV, PRIORITY-QMin, PRIORITY-QFreq and PRIORITY-QMax order fulfillment polices are given in Table 6-2 and Table 6-3. Another important statistic collected in the experiment is the service levels within the network. These results are summarized in Figure 6-13 and Figure 6-14. The experimental results illustrate that order fulfillment policy plays an important role in determining the customer service level. In order to gain a better understanding of the effect of order fulfillment strategy, the study selected three distribution centers to suffer from backorder: RDC6, RDC15, and RDC17. Although these policies do not make a substantial difference in the customer service levels of DCs, Figure 6-13 and Figure 6-14 show that the priority rule may have a significant impact on performance of selected RDCs.

Table 6-3: Cost Performance Measures of Exp-Set-3 under Different Queueing Policy

Priority	Holding Cost	Shortage Cost	Order Cost	Transport Cost	Activity Cost	Total Cost (€)
FCFS	3%	56%	5%	25%	11%	18,607,284
CV	3%	53%	5%	27%	12%	17,339,611
QMin	3%	61%	4%	22%	10%	20,752,795
QFreq	3%	61%	4%	22%	10%	20,696,718
QMax	5%	26%	8%	43%	18%	11,272,318

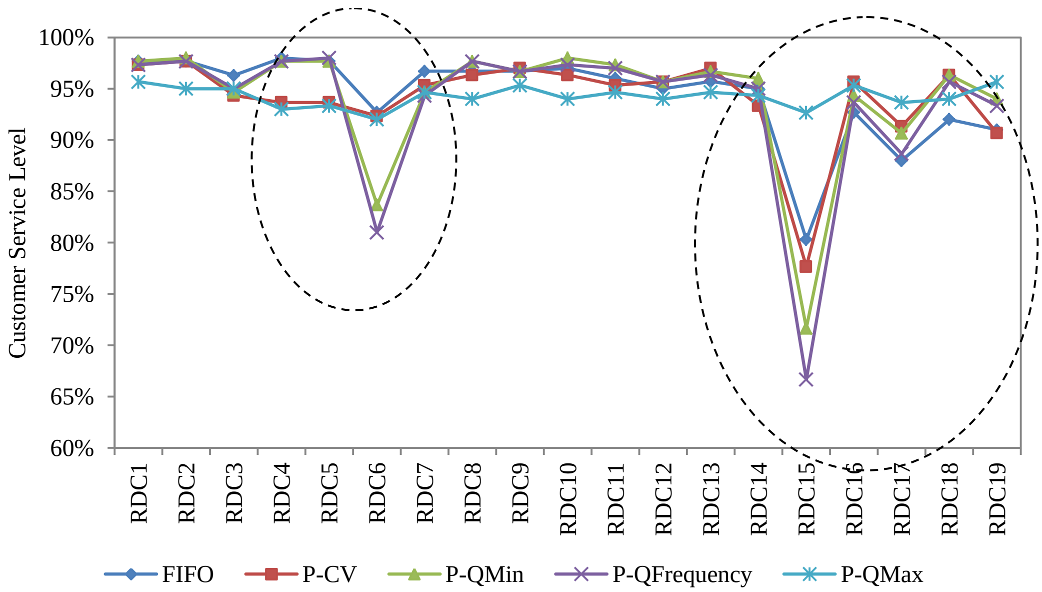


Figure 6-13: Performance of different order fulfillment strategies for RSDT replenishment policy

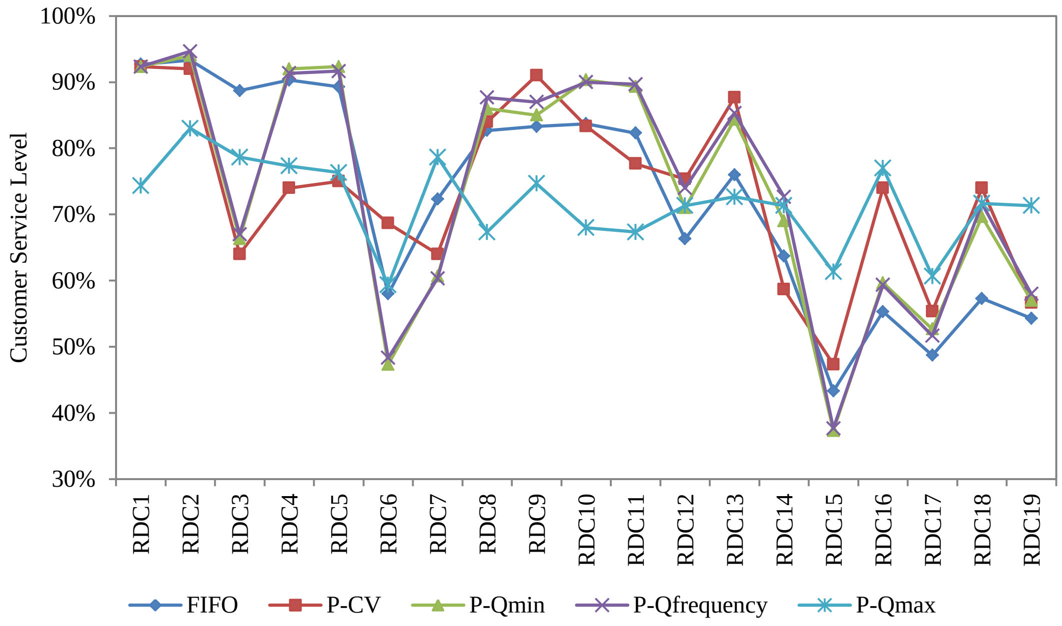


Figure 6-14: Performance of different order fulfillment strategies for RQMAX replenishment policy

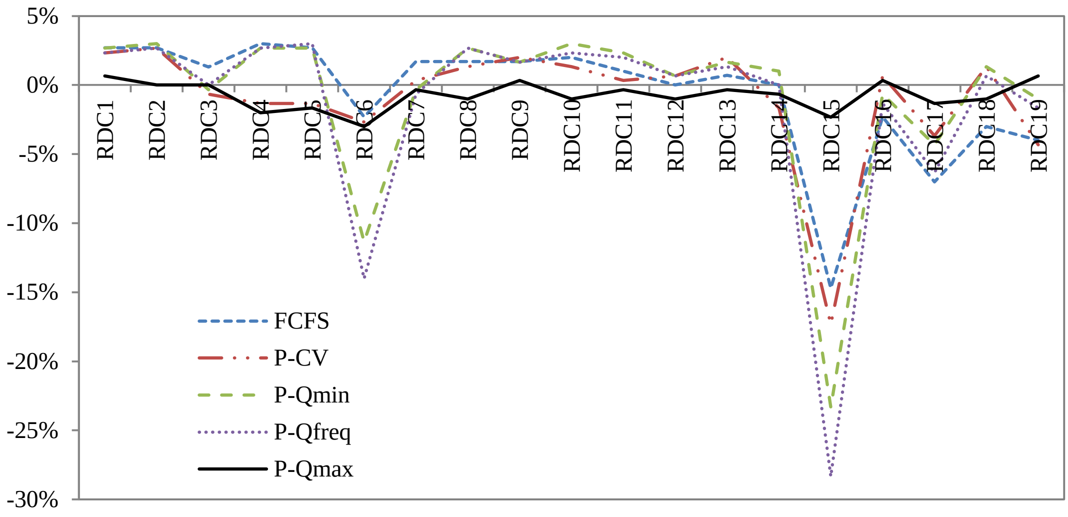
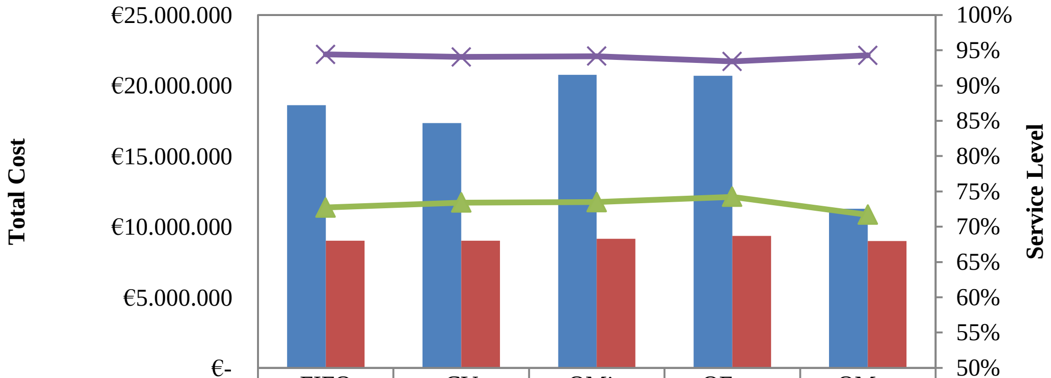


Figure 6-15: The Gap between Target Service Level and Simulated Service Level among the whole Supply Chain under RSDT replenishment policy

One of the interesting observations from Figure 6-16 is that there are cases where the FCFS and PRIORITY-QFreq policy outperforms the other priority policies. Furthermore, in the cases that the FCFS and PRIORITY-QFreq policies result in a higher fill rate than the fill rate of the PRIORITY-QMax policy in multi-echelon inventory systems, the cost of PRIORITY-QMax policy is lower than the FCFS and PRIORITY-QFreq policies. The main reason is that the PRIORITY-QMax scenario has relatively low stock-out cost (see Table 6-2 and Table 6-3). The PRIORITY-QMax concept seems to have a stabilizing effect on the system's service level performance.

Using this strategy, the average fill rate is increasing due to a decrease in the average waiting time at the upper echelon. To analyze this fact in more detail, Table 6-4 summarizes performance measures for selected DCs.



	FIFO	CV	QMin	QFreq	QMax
RQMax	€18.607.284	€17.339.611	€20.752.795	€20.696.718	€11.272.318
RSDT	€9.000.686	€9.010.048	€9.133.102	€9.337.786	€8.975.906
RQMax-FillRates	72,711%	73,421%	73,491%	74,228%	71,702%
RSDT-FillRates	94,400%	94,053%	94,158%	93,404%	94,263%

Figure 6-16: Comparison of Customer Prioritization on Performance

Table 6-4: Service Level Performance Results for RDC6, RDC15, and RDC17 under Different Replenishment Policy and Order Fulfillment Strategy

	RDC6			RDC15			RDC17		
	Exp-Set-1	Exp-Set-2	Exp-Set-3	Exp-Set-1	Exp-Set-2	Exp-Set-3	Exp-Set-1	Exp-Set-2	Exp-Set-3
QFreq	93%	84%	86%	86%	63%	77%	84%	49%	69%
QMin	91%	83%	84%	85%	65%	72%	86%	54%	63%
CV	94%	89%	92%	88%	71%	70%	88%	66%	68%
QMax	95%	86%	90%	93%	89%	92%	95%	88%	93%
FCFS*	92%	92%	92%	80%	70%	60%	88%	81%	80%

*Base Experiment

6.4 Summary

This section has presented the simulation studies that compare the performance of different strategies for the multi-echelon production-inventory system. It has structured the model based on a multi stage divergent inventory system with a capacitated production facility. Firstly, the impact of different inventory allocation decisions of the plant-WRs on the supply chain performance measures is analyzed. These approaches involve the specification of the reorder point for upper echelons, such that the predetermined lot size is triggered whenever the net stock position drops to the reorder point. It is found that for similar operating conditions and for similar performance records, the RHSUMQ policy tends to perform better than the corresponding reorder point policies. The change in the relative fill rate performance of RHSUMQ compared to the base experiment seems to be significant since the change in the cost is relatively low. In addition, a relationship between the order fulfillment policy and the customer service level has been showed. According to the experimental results, customer prioritization polices can reduce the total system cost in comparison to FCFS as they increase the customer service level. One of the key findings in this chapter is that using FCFS strategy can lead to unstable performance within the supply chain.

Chapter 7

Simulation-Based Optimization for Multi-echelon Inventory Problems

Simulation modeling has recently become a major tool since an analytical model is unable to formulate a system that is subject to both variability and complexity. However, simulations require extensive runtime to evaluate many feasible solutions and to find the optimal one for a defined problem. To deal with this problem, simulation model needs to be integrated in optimization algorithms. (Keskin et al., 2010). This chapter describes the design of a framework to carry out simulation-based optimization of the inventory parameters of a multi-echelon production-inventory system. A brief description of simulation-based optimization approach is presented in Section 7.1. Section 7.2 presents the classification of simulation-based optimization methods. The details of the proposed multi-objective metaheuristics for simulation-based optimization approach are given in Section 7.3. Section 7.4 demonstrates the application of the introduced framework for a simulation-based optimization with a real case study.

7.1 Introduction to Simulation-Based Optimization

Simulation-based optimization (SBO) is the process of obtaining optimal set of control variables, where the objective functions and performance of the system are generated as a result of the simulation model over the system (Olafsson & Kim, 2002). Figure 7-1 illustrates the general scheme of the simulation-based optimization procedure. In the context of SBO, the optimization engine includes upper and lower bounds for input parameter, the optimization objectives with corresponding constraints, and the optimization algorithms, while the simulation model incorporates the system parameters, the representation of the real system with its boundaries, the internal and external factors, and their relationship within the system (Aslam, 2013). In contrast to traditional optimization approaches, in SBO, the performance measure generated by a simulation model becomes the output of objective function instead of an analytical function of decision variables (Ammeri et al., 2010), (Mele et al., 2006).

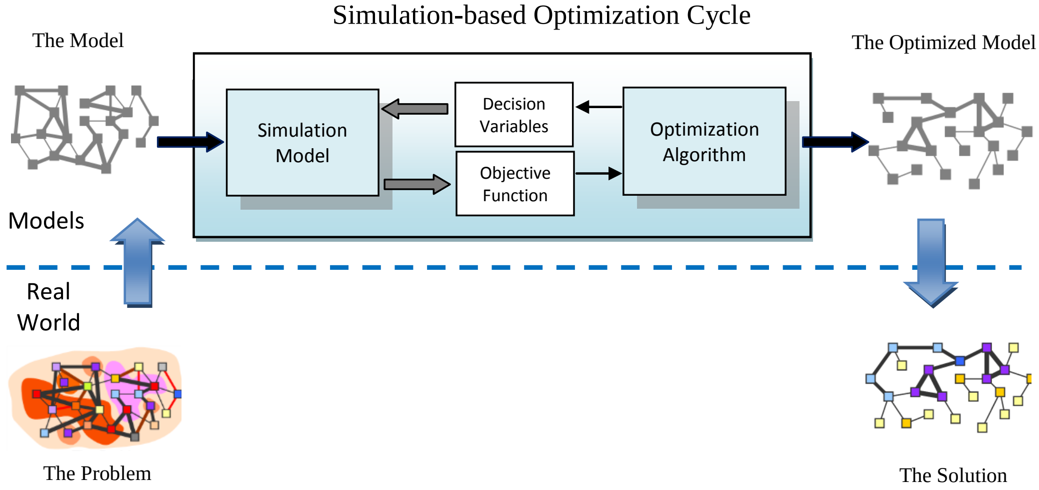


Figure 7-1: Simulation-Based Optimization Scheme (adapted from (Borshchev & Filippov, 2004))

SBO is an iterative process that is used to find the best solution to stochastic problems among different sets of decision variables leading to optimal performance without explicitly evaluating each possibility (Carson & Maria, 1997). In the SBO environment, the input parameters and the structural assumptions associated with a simulation model are factors that become decision variables. The output performance measures are responses used to model an objective function and constraints (April et al., 2003). While the main aim of simulation is to find out which factors have the greatest effect on a response, optimization seeks to identify the combination of factors that minimizes or maximizes a response. As mentioned earlier, the proposed SBO framework consists of two components as shown in Figure 7-1: an optimization tool and a simulation tool. In the context of SBO, the simulation is initiated through receiving a set of candidate decision variables generated by the optimization engine. After receiving the input values from the optimization engine, the simulation is executed to transform input variables into valuable information (performance measures) by evaluating of each candidate solution. The performance measures are then fed back to optimization engine to generate another set of new solutions for the decision variables that seeks to improve the performance of the system. This procedure is run iteratively until the pre-specified stop criterion is reached, which might be that objective values have been reached, a certain amount of time has passed or a requested number of loops has been performed (Syberfeldt, 2009).

7.2 Classification of the Simulation-Based Optimization Methods

Carson and Maria (1997) identify 6 major categories for simulation optimization methods:

- Gradient Based Search Methods
- Stochastic Optimization (Simple Path Optimization)
- Response Surface Methodology
- A-Team
- Statistical Methods
- Heuristics Methods

Gradient based search methods estimate the gradient of response function in order to determine a search direction and use deterministic mathematical programming techniques. Gradient based search methods are used for continuous variable problems due to its close relationship with the steepest descent gradient search (April et al., 2003). The well-known gradient estimation methods used in the literature are: finite difference estimates; perturbation analysis; frequency domain analysis; and likelihood ratio estimates.

Stochastic optimization is a procedure of finding a local optimum for an objective function whose values are not known analytically but can be estimated or measured. This method use recursive schemes based on gradient estimation (Carson & Maria, 1997). The main disadvantage of stochastic optimization is that a large number of iterations of the recursive formula is needed to come up with the optimum (Tekin & Sabuncuoglu, 2004).

Response Surface Methodology (RSM) is a procedure for fitting a series of regression models to the output variable of a simulation model (by evaluating it at several input variable values) and optimizing the resulting regression function (Carson & Maria, 1997). The first step in RSM involves determining the order regression function. The steepest ascent or descent search method is then employed to reach the optimum. Once the region of the optimum has been found, this method can employ higher degree regression functions. In general, RSM is a relatively efficient method of simulation-based optimization in the number of simulation experiments needed, particularly when compared to gradient search methods (Tekin & Sabuncuoglu, 2004).

Statistical methods are often used to solve integer valued optimization problems (Joshi et al., 1996). The most popular statistical methods are ranking and selection, multiple comparisons, and sampling methods. The basic idea of the sampling method is to simulate the system with different underlying probability measures so as to increase the probability of simulating typical paths of interest (Carson & Maria, 1997). For each observation during the simulation, the estimated measure is multiplied by a correction factor to obtain an unbiased estimate of the measure in the original system. Ranking and selection methods are employed when comparisons among a finite and typically small number of systems are required (Ahmed & Alkhamis, 2002). A ranking and selection procedure selects the best system from a set of competing systems.

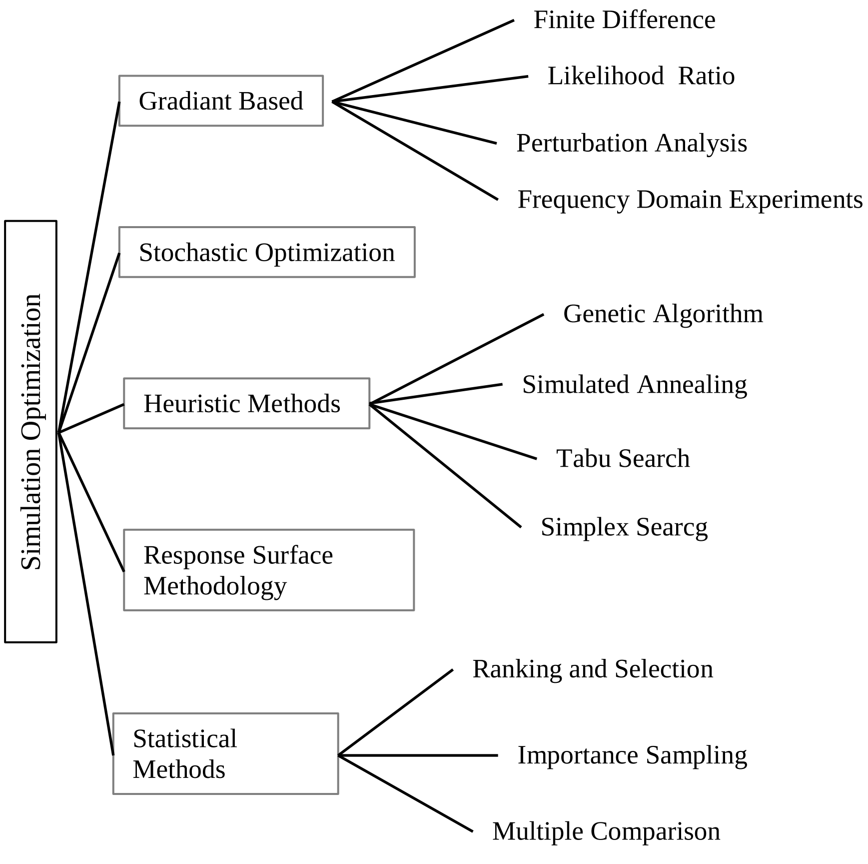


Figure 7-2: Taxonomy of existing simulation-based optimization approaches (Carson & Maria, 1997)

All of the techniques discussed above are local search techniques. Among the most practical approaches that employ SBO are metaheuristics methods, including genetic algorithms; ant colony optimization; tabu search; simulated annealing; scatter search; and random hill climbing. Metaheuristic methods are emerging as successful alternatives to traditional approaches for solving complex optimization problems with many local optima where other optimization methods have failed to be either effective or efficient (Olaffson, 2005). These methods start by obtaining an initial solution or an initial set of solutions, then initiating an improving search guided by a certain principle.

In the following we focus our interest on the metaheuristics approaches to the inventory optimization problem.

7.3 Multi-Objective Optimization via Simulation

Optimization problems with two or more conflicting objectives arise in the design, modeling, and planning of many complex real systems. One of the most important aims of multi-objective optimization is to obtain feasible solutions that balance several conflicting objectives. However, it is difficult to find such a solution due to the realities of addressing real-world problems. The time required to solve multi-objective supply chain problems stretches to become unpalatably long as the number of variables increases. To overcome this challenge, the use of metaheuristics has received increasing attention from the research community over the last decade. The motivation for using metaheuristic algorithms is to produce efficient solutions to supply chain optimization problems with a reasonable amount of computational time. One simple example of a class of supply chain multi-objective optimization problems is the inventory control problem. This section investigates the possibility of applying multi-objective metaheuristic algorithms to a simulation-based optimization approach for a multi-echelon production-inventory system. Chapter 3 reviewed a number of general metaheuristic algorithms in the literature. An introduction to multi-objective metaheuristic algorithms based on GA and PSO used to find optimal solutions was given in Section 3.3. The two metaheuristic algorithms, which are under investigation in this section, are NSGA-II and MOPSO, which show strong performance in solving multi-objective optimization problems. In this study, both algorithms are developed in an object-oriented manner using C-Sharp for modeling flexibility and execution efficiency. Figure 7-3 shows the black-box approach to simulation based optimization for inventory problems. The methodology used for solving multi-objective inventory problems involves two phases (Niranjan, 2008):

- At the first phase, to generate possible the reorder point and the order quantity of each stock point in the network based on the upper and lower bounds, NSGA-II and MOPSO algorithms are.
- At the second phase, the developed object-oriented simulation model is used to compare the performance of system under different decision variables. The performance is measured according to different criteria: customer service level, fill rate, number of backordered items, and total cost.

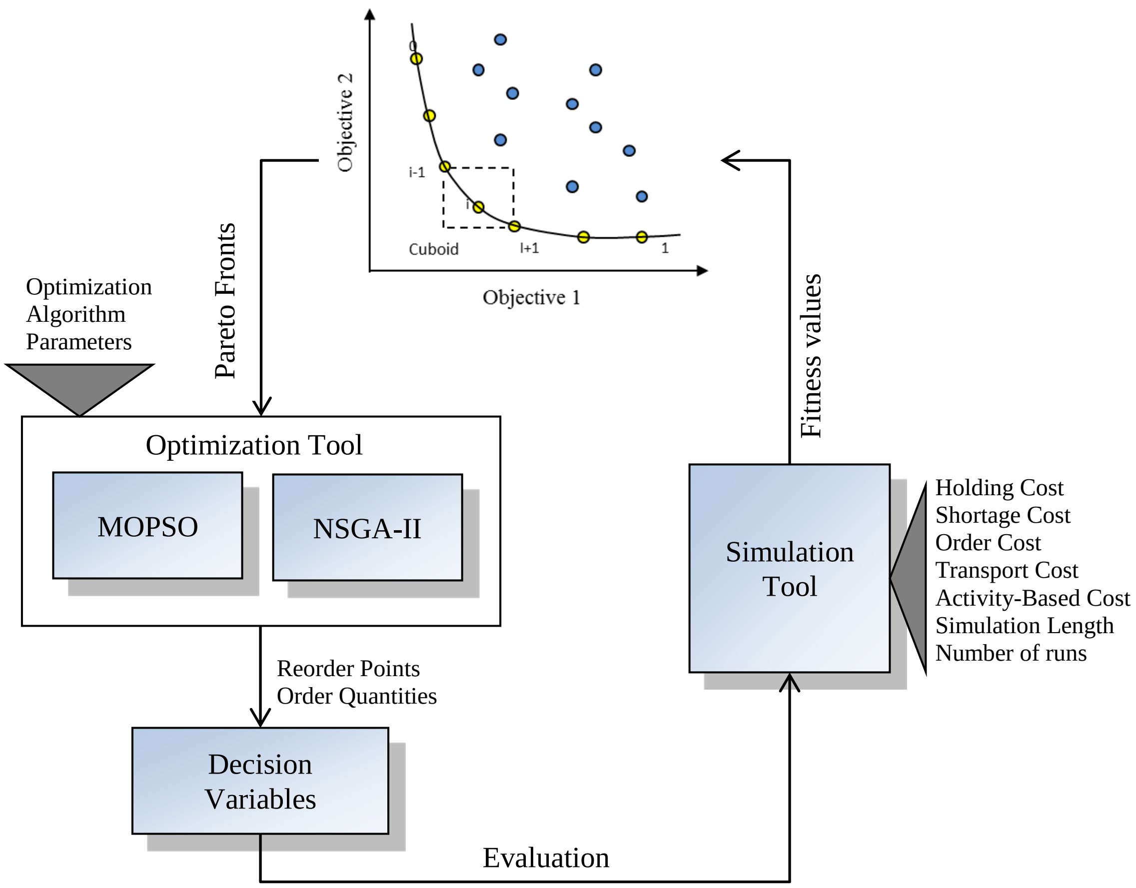


Figure 7-3 Simulation-Based Optimization Scheme for Inventory Problem

At the optimization phase, the optimization tool explores the search space within a loop. Each examined search space point (i.e., a set of decision variables) is delivered to the simulation model to estimate the performance of each location within the system. Once the simulation is complete, objective values are assigned to each location corresponding to their performance and exported from simulation phase into optimization phase. The result of a successfully terminated optimization phase is a list of decision variables. The optimization loop is repated until the stop criterion is fulfilled. The choice of stopping criteria can significantly influence the duration of an optimization run. There are three stopping criteria applied in the literature: i) stop with fitness value, ii) stop with fitness change, and iii) stop with time (maximum generation number) (Yu & Gen, 2010). The main difficulty in designing termination criteria is determining a reasonable value for that number such that convergence to the optimal solution is guaranteed with a certain confidence level (Safe et al., 2004). Due to varied stopping criteria, an optimization method might be unable to converge in a given termination condition, or the optimization method may waste computational resources because of processing unnecessary optimization runs.

7.3.1 Multi-Objective Simulation-based Optimization based on GA (NSGA-II-SO)

The proposed framework named multi-objective simulation-based optimization using genetic algorithms (NSGA-II-SO) utilizes a population-based evolutionary algorithm. Each solution of NSGA-II algorithm is represented by an n-dimensional vector $X = (x_1, x_2, \dots, x_n)$, where n is equal to the number of decision variables of the problem under study. A decision variable x_i is randomly generated according to a given lower bound and upper bound. Figure 7-4 shows the flowchart of NSGA-II-SO. In Phase 1, which is the NSGA-II run, the algorithm starts the search by generating a population of candidate solutions. Each chromosome in the population is evaluated through simulation in Phase 2 and ranked to form non-dominated fronts according to the dominance concept. Evaluated and sorted chromosomes are then selected for recombination by using binary tournament selection. Under this scheme, two chromosomes are selected at random from the current population, and their fronts are compared. The chromosome, which is in a lower domination frontier set, is selected as a parent for crossover. During the selection, the crowding distance comparator is used to select chromosomes, if both chromosomes belong to the same front. Next, the algorithm applies crossover and mutation operators on selected parents to generate the next generation. The algorithm runs until user-defined termination is satisfied.

7.3.2 Multi-Objective Simulation-based Optimization based on PSO (MOPSO-SO)

Another metaheuristic under consideration in this research is multi-objective Particle Swarm Optimization (MOPSO). Using MOPSO as the mechanism to perform multi-objective simulation-based optimization requires implementing the form of NSGA-II-SO described in previous section with some modifications. Particle Swarm Optimization (PSO) is similar to the Genetic Algorithm (GA) in the sense that these two techniques are population-based search methods and they search for the optimal solution by updating generations (Panda & Padhy, 2008). Like NSGA-II-SO, MOPSO-SO begins its search from a randomly generated population. After the positions and velocities of particles are initialized, the objective functions are evaluated via simulation for each particle, as described in NSGA-II-SO. The concept of Pareto dominance is applied to sort the solutions. The set of non-dominated solutions are all stored in an external archive, in which the best non-dominated solutions are kept. MOPSO-SO applies two operators to obtain its new population: velocity update and position update. Each particle randomly selects a non-dominated solution from the archive for the social influence to update its velocity and position. The general flowchart of the simulation-optimization based on MOPSO is illustrated in Figure 7-5. We refer the reader to the Section 3.3.2 for more details.

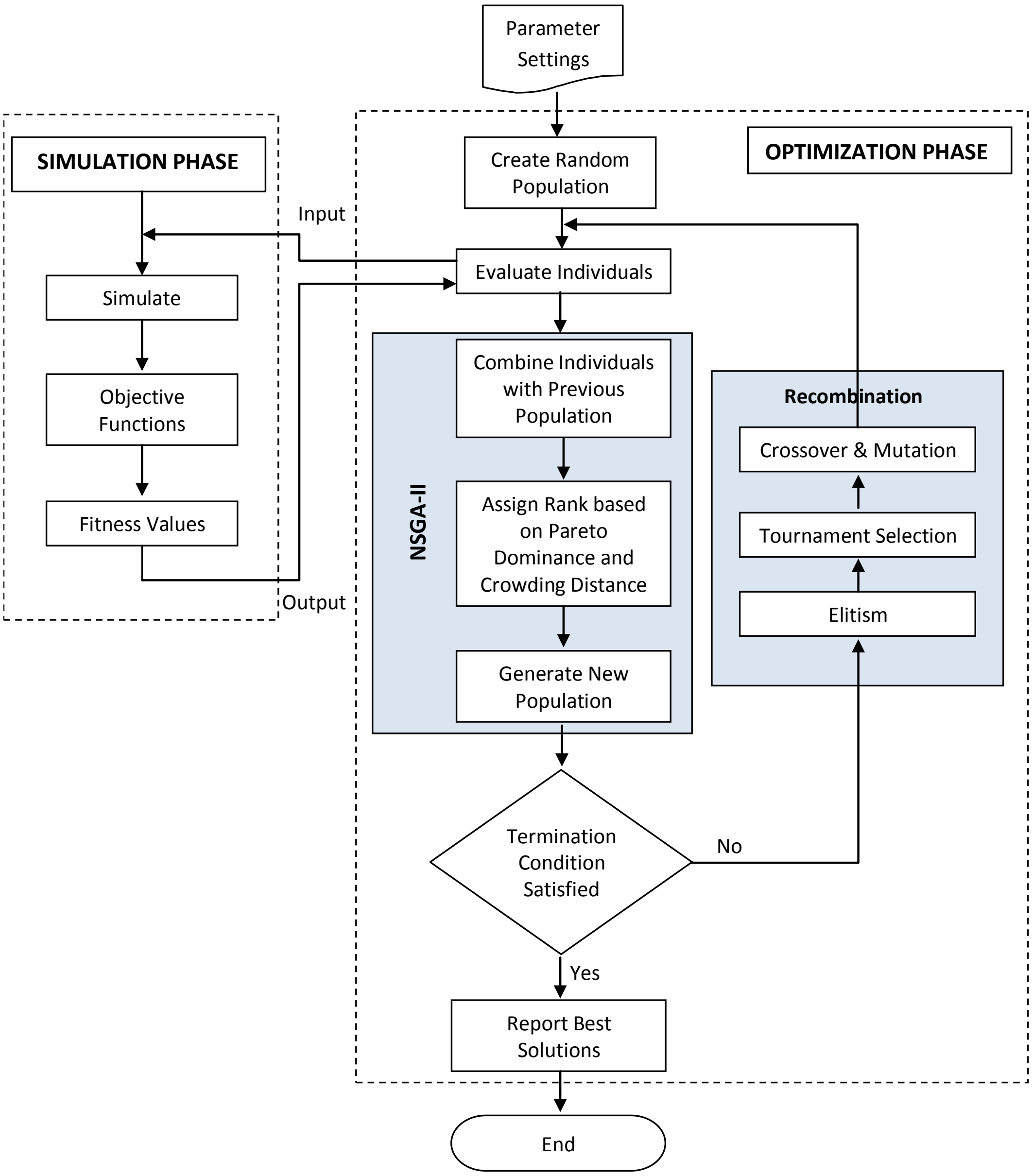


Figure 7-4: Flowchart of the simulation optimization based on NSGA-II (NSGA-II-SO)

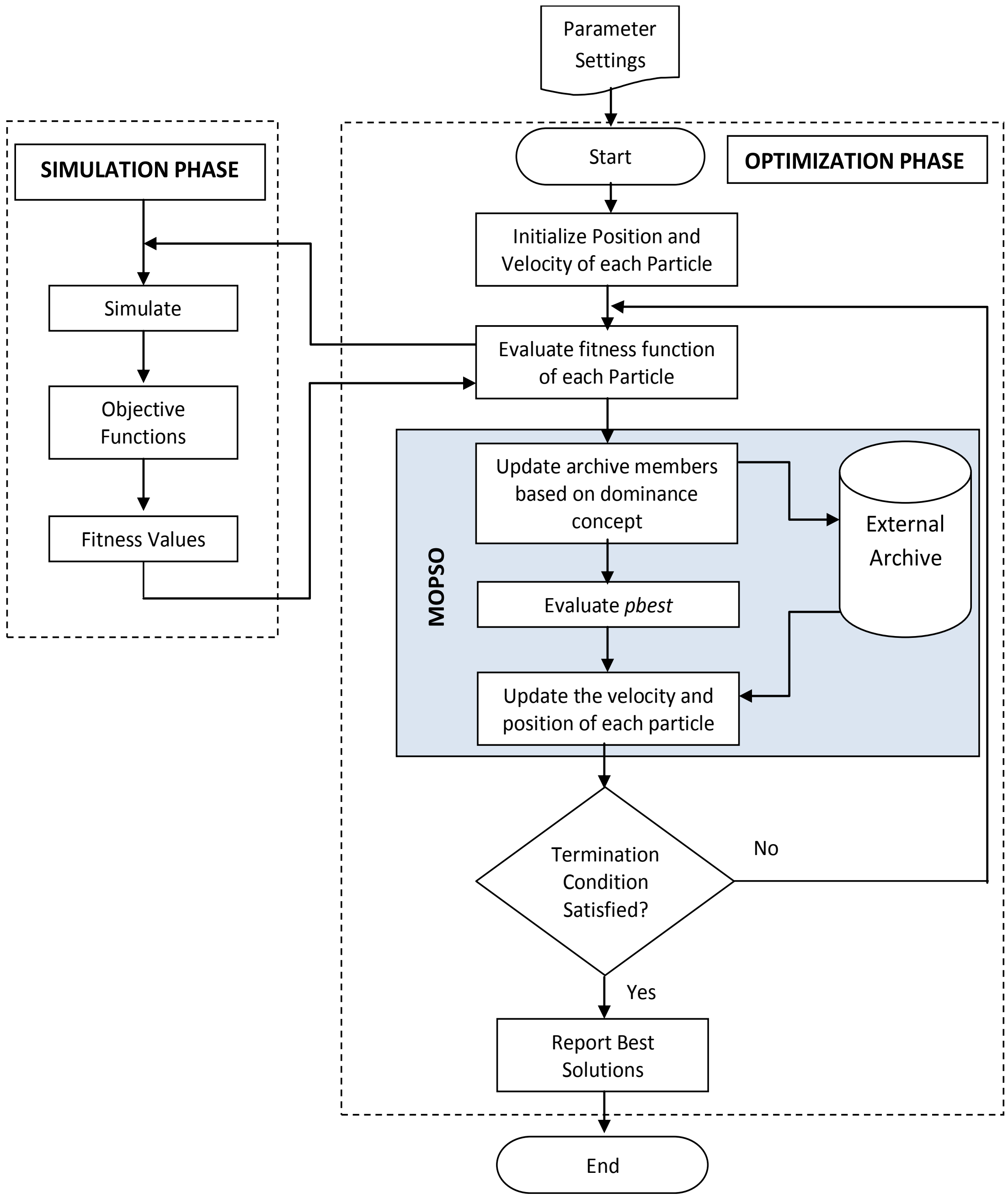


Figure 7-5: Flowchart of the simulation-optimization based on MOPSO (MOPSO-SO)

7.4 Implementation of Simulation-Based Optimization for Inventory Problems

This section discusses parameter optimization of the production-inventory system in a multi-echelon supply chain via SBO. The particular focus is a common problem in supply chain management, i.e., the determination of inventory control parameters at each stock point. However, the stochastic environment makes it difficult for companies to determine the optimal inventory system.

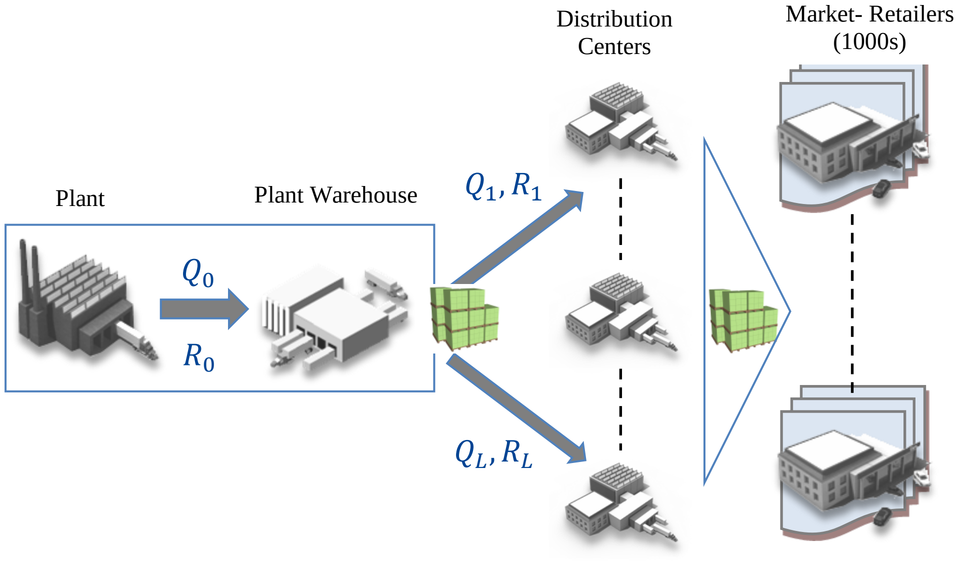


Figure 7-6: Two-echelon divergent production-inventory system

The integrated approach combines the object-oriented simulation tool for performance evaluation with metaheuristics for optimization. We examine an inventory problem for a grocery product supply chain described previously by considering the problem as a multi-objective non-linear inventory optimization problem in which a single product is produced to fulfill stochastic demands over a finite planning horizon of T periods (i.e. days). Considering three plant warehouses, Plant-WR1, Plant-WR2, and Plant-WR3, all offer different products to their local DCs as shown in Figure 7-6. To examine the method for obtaining a set of Pareto frontiers, the two primary objectives for optimizing the system are minimizing inventory level while maximizing customer service level.

7.4.1 Model Assumptions

A real-coded GA and PSO are implemented to avoid the difficulties associated with binary representation and bit operations, particularly when dealing with continuous search spaces that have large dimensions. An individual (or a chromosome) in both algorithms represents an array of inventory decision variables for the problem under study. In an n-facility supply chain problem, the decision variables for the optimization procedure include an order quantity vector $[Q_1, Q_2, \dots, Q_n]$ and a reorder point vector $[R_1, R_2, \dots, R_n]$. The initial population is generated randomly based on the upper and lower bound for each of the decision variables using a uniform distribution $U[R_i^{LB}, R_i^{UB}]$ and $U[Q_i^{LB}, Q_i^{UB}]$.

Table 7-1: Search control parameters for NSGA-II and MOPSO

Parameter for NSGA-II	Value	Parameter for MOPSO	Value
Population Size	100	Population Size	50
Generation	100	Generation	100
Crossover Rate	0.8	Archive Size	40
Mutation Rate	0.2	Local Coefficient	2
Elitism Count	2	Global Coefficient	2
Crossover Type	UNIFORM	Velocity Interval	5
Mutation Type	UNIFORM	Max. Inertia Weight	0,9
		Min. Inertia Weight	0,2
Simulation Period		365 days	
Simulation Replication		10 replications	

The upper bound for order quantity considers the physical warehouse stocking capacity, which equals 15 days of average daily demand. The lower bound is assumed to be one pallet. Reorder point limits are computed by accounting for customer demand, maximum replenishment lead time, and safety stock. The maximum replenishment lead time for a location is the sum of the replenishment lead time of the location itself and the lead time of all upstream locations (L_e= echelon lead time). Maximum safety stock is calculated with maximum service level ($k = 3{,}72$). Hence the upper limit of the reorder point is computed as below:

$$R_1^{UB} = \mu \times (L_e) + k \times \sigma \times \sqrt{(L_e)} \tag{7-1}$$

The proposed genetic algorithm and particle swarm optimization is implemented in C-Sharp under a Visual Studio.net environment. The control parameters for the real-coded NSGA-II and MOPSO are summarized in Table 7-1.

7.4.2 Experimental Results and Discussion

The proposed MOPSO-SO and NSGA-II-SO approaches have been implemented to optimize daily inventory cost and customer service level objectives simultaneously considering the three plant-warehouses stated above. The results report includes the optimal Pareto front and related inventory control parameters of each solution point in Pareto front. The distribution of the Pareto optimal set over the trade-off surface is shown in Figure 7-7, Figure 7-8 and Figure 7-9. The figures reveal that solutions are widely distributed over the Pareto-optimal front due to the diversity of the non-dominated solutions in the proposed MOPSO-SO technique, and the problem of concern is solved effectively. Two non-dominated solutions that represent the best cost and best customer service level with related inventory parameters are given in Table 7-2.

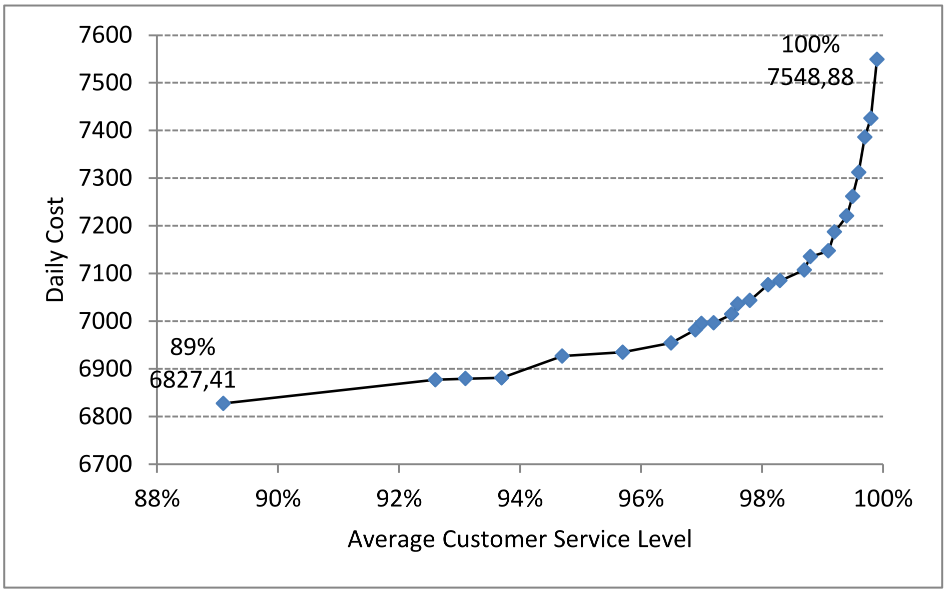


Figure 7-7: Final Pareto front of MOPSO-SO for the network of Plant-WR1

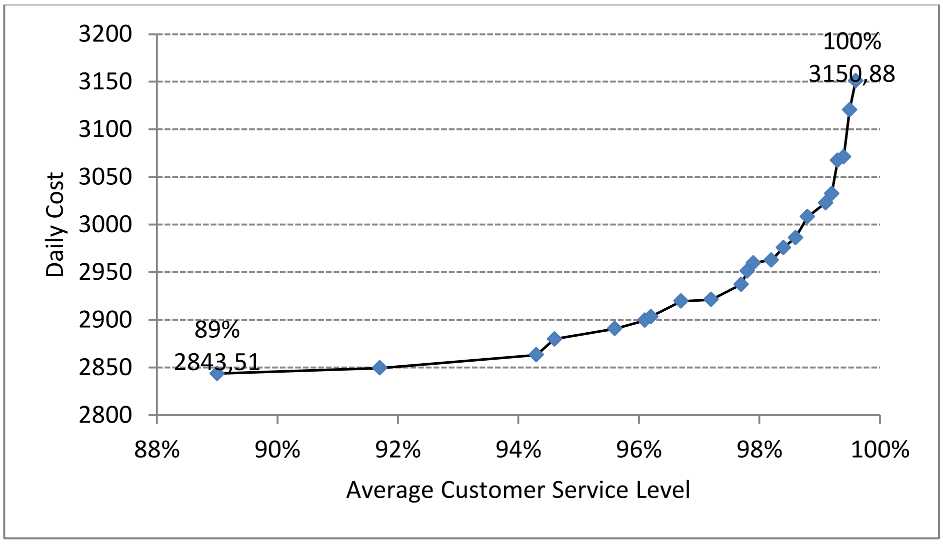


Figure 7-8: Final Pareto front of MOPSO-SO for the network of Plant-WR2

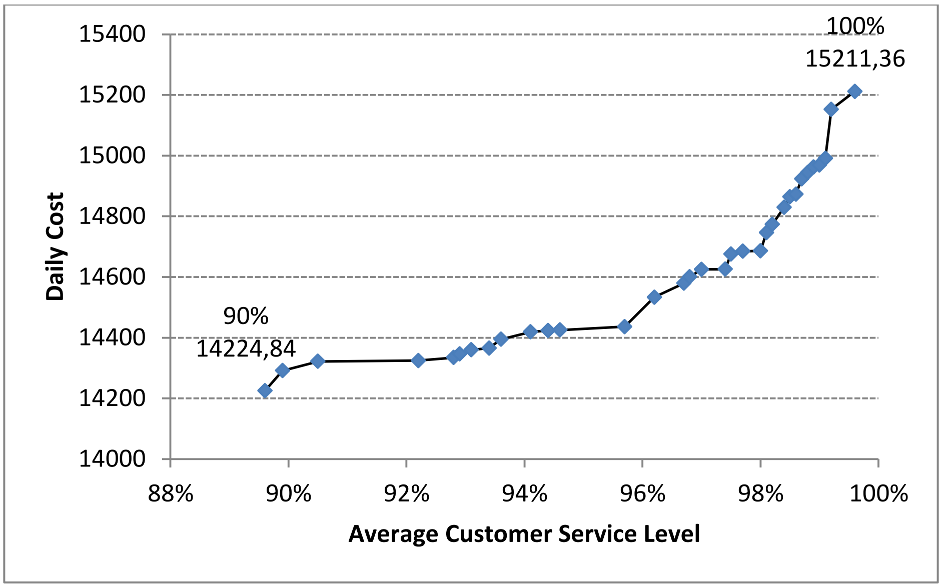


Figure 7-9: Final Pareto front of MOPSO-SO for the network of plant-WR3

For example, for Plant-WR3, the service level of 100% produced a daily cost of 15,211 € while 90% service level produced a daily cost of 14,225 €. From the best identified inventory parameters in these tables, it can be seen that as the end-customer service level increases, the best identified reorder points also increase at each node. However, changes in order quantities are relatively small.

Table 7-2: The Best Cost and Best Service Level of proposed MOPSO-SO for Network of Plant-WR1, Plant-WR2, and Plant-WR3

Plant-WR1					
Daily Cost FillRate	6.827 € 89%		Daily Cost FillRate	7.549 € 100%	
Node	**R**	**Q**	**Node**	**R**	**Q**
RDC1	24	75	RDC1	43	107
RDC2	27	66	RDC2	39	81
RDC3	37	81	RDC3	55	94
RDC4	24	62	RDC4	37	81
RDC5	5	100	RDC5	38	123
RDC6	68	136	RDC6	101	184
RDC7	30	109	RDC7	66	90
RDC8	28	69	RDC8	63	43
RDC9	48	79	RDC9	72	131
RDC10	35	75	RDC10	45	95
RDC11	43	91	RDC11	58	134
RDC12	34	145	RDC12	64	145
RDC13	34	102	RDC13	65	110
RDC14	31	148	RDC14	63	110
RDC15	90	149	RDC15	112	80
RDC16	40	108	RDC16	71	108

RDC17	35	259	RDC17	92	216
RDC18	53	137	RDC18	52	191
RDC19	47	133	RDC19	68	129
Plant-WR1	155	1523	Plant-WR1	837	2021
Plant-WR2					
Daily Cost FillRate	2.844 € 90%		Daily Cost FillRate	3.151 € 100%	
Node	**R**	**Q**	**Node**	**R**	**Q**
RDC1	11	34	RDC1	22	40
RDC2	5	39	RDC2	11	25
RDC3	10	78	RDC3	35	110
RDC4	9	33	RDC4	12	43
RDC5	13	35	RDC5	14	54
RDC6	13	99	RDC6	46	92
RDC7	20	62	RDC7	22	113
RDC8	15	54	RDC8	17	50
RDC9	11	60	RDC9	14	102
RDC10	14	40	RDC10	16	66
RDC11	10	37	RDC11	17	53
RDC12	11	72	RDC12	24	87
RDC13	14	67	RDC13	19	74
RDC14	10	65	RDC14	20	59
RDC15	30	77	RDC15	46	115
RDC16	11	69	RDC16	29	43
RDC17	16	78	RDC17	31	106
RDC18	9	66	RDC18	19	72
RDC19	22	102	RDC19	21	101
Plant-WR2	130	1805	Plant-WR2	525	1186
Plant-WR3					
Daily Cost FillRate	14.225 € 90%		Daily Cost FillRate	15.211 € 100%	
Node	**R**	**Q**	**Node**	**R**	**Q**
RDC1	46	147	RDC1	85	88
RDC2	50	136	RDC2	71	134
RDC3	128	211	RDC3	146	212
RDC4	58	110	RDC4	70	174
RDC5	46	70	RDC5	68	129
RDC6	150	281	RDC6	224	333
RDC7	89	156	RDC7	144	174
RDC8	65	144	RDC8	114	199
RDC9	61	180	RDC9	105	217
RDC10	63	211	RDC10	90	93
RDC11	66	141	RDC11	98	184
RDC12	104	132	RDC12	114	200
RDC13	46	222	RDC13	89	236
RDC14	58	198	RDC14	114	176

RDC15	226	241	RDC15	245	195
RDC16	111	183	RDC16	150	224
RDC17	88	224	RDC17	228	258
RDC18	66	212	RDC18	108	198
RDC19	87	214	RDC19	157	165
Plant-WR3	926	1470	Plant-WR3	1600	1932

7.4.3 Comparison of NSGA-II-SO and MOPSO-SO

Evaluating the performance of developed optimization algorithms is a crucial task in order to compare with other algorithms. Many quantitative performance metrics have been proposed in the literature to address this issue. The main criteria in the multiobjective algorithm are the convergence to the Pareto front and with the respect to the diversity of the obtained solutions (Carrasqueira et al., 2015). Three quantitative measures have been commonly used in evolutionary algorithms literature, i.e., generational distance (GD), spacing metric (SP), and the number of non-dominated solutions (NSM). These performance measures show how the average or best fitness values or some other performance metric is varying with different parameter settings. In this section, the performance of the proposed approach is evaluated using mentioned metrics.

Generational distance (GD): Van Veldhuizen and Lamont (1998) suggested the Generational Distance (GD) metric that determines if all of the solutions are also within the optimal Pareto front, which is given by

$$GD = \frac{1}{n}\sqrt{\sum d_i^2} \qquad \text{7-2}$$

n is the number of vectors in the set of nondominated solutions found so far and d_i is the Euclidean distance between the solution i and the nearest member of the Pareto optimal set. As it can be understood from its equation, the GD represents the average distance between the each solution in the Pareto front and its nearest neighbor in the optimal Pareto front. If the GD = 0, it means all the solutions generated are in the Pareto optimal front. If they are not contained in the Pareto front being evaluated, then the GD > 0, which indicates how “far” the solutions are from the optimal Pareto front.

Spacing metric (SP): The Spacing Metric (SP) proposed by Schott (1995) is another way to measure the performance of a multiobjective algorithm, which indicates how uniformly the points in the approximation set are distributed in the objective space (Radhi & Barrans, 2012). It is mathematically expressed as:

$$SP = \sqrt{\frac{1}{n-1}\sum(\bar{d} - d_i)^2} \tag{7-3}$$

where d_i represents the Euclidean distance between two consecutive members in Pareto front and $\bar{d}$ is the mean value of the distance measure. A smaller value for this metric is the ideal one and it indicates that all members of the Pareto front obtained so far are uniformly spread among the Pareto front.

Non-dominated Solutions Metric (NSM): This metric compares the number of non-dominated solutions that are obtained by each algorithm.

Figure 7-10 depicts the Pareto surfaces obtained using MOSP and NSGA-II to optimize daily inventory cost and customer service level. According to the Figure 7-10, it shown graphically that MOPSO-SO is able to finds better spread of solution set along the front and a better convergence measure than NSGA-II-SO. Table 7-3 show the means, variances and statistics of three performance metrics obtained over the 10 independent runs using the two optimization algorithms. A point that should be highlighted from the table is that the MOPSO-SO gives better results with good diversity and convergence for lower number of population.

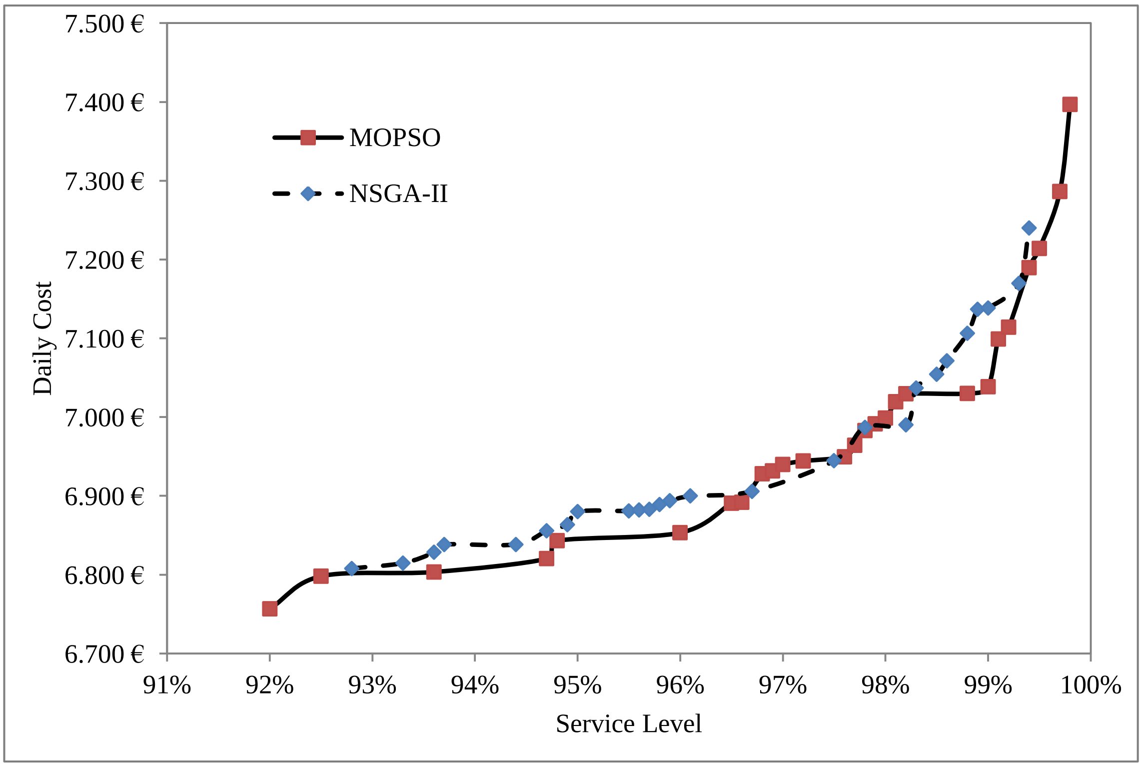


Figure 7-10: The Pareto Fronts generated by Two Algorithms

Performance metrics mentioned above are generally related to the diversity and spread of the solutions in the objective space. However, these methods are not able to guarantee that solutions obtained will apply across diverse populations in the decision space (Güller et al., 2015). Several researchers in the literature have investigated that many existing evolutionary algorithms suffer from the premature convergence/stagnation phenomenon (Carter & Park, 1994) (Hu, 2004). As a matter of fact, population based algorithms tend to stagnate due to an inability to generate new promising search directions in large-scale problems (Weber et al., 2011). In order to distinguish how the stagnation phenomenon may happen, the non-dominated solutions for RDC5 and RDC11 in the decision search space are selected (see Figure 7-11).

Table 7-3: Comparison of results between NSGA-II-SO and MOPSO-SO

	MOPSO-SO			NSGA-II-SO		
	GP	SP	NSM	GP	SP	NSM
Best	0,054335995	0,0385161	27	0,059712	0,038969	27
Worst	0,065091045	0,081419	22	0,073655	0,085233	21
Average	0,06100552	0,058095	23,63	0,068712	0,062101	24,3
Median	0,060711505	0,0603356	23,5	0,0714253	0,070983	24
SD	0,0038454	0,0141848	1,7678	0,003414	0,009858	1,6517

As it can be seen from the figure, as the non-dominated solutions of MOPS-SO spread among the search space, NSGA-II-SO leads to stagnation due to loss of diversity in the population. Further, the algorithms are also compared in terms of running time. The execution time of the two algorithms increases significantly when the population and generation numbers rise. It is important to notice the very high speed of MOPSO-SO, which requires considerably less time than the NSGA-II-SO in the problem.

Table 7-4: Comparison of CPU time between NSGA-II and MOPSO

			NSGA-II	MOPSO
	Generation	Population Size	CPU Time (second)	CPU Time (second)
1	10	10	59.4	46.3
2	50	10	312	233
3	50	50	1867	1462

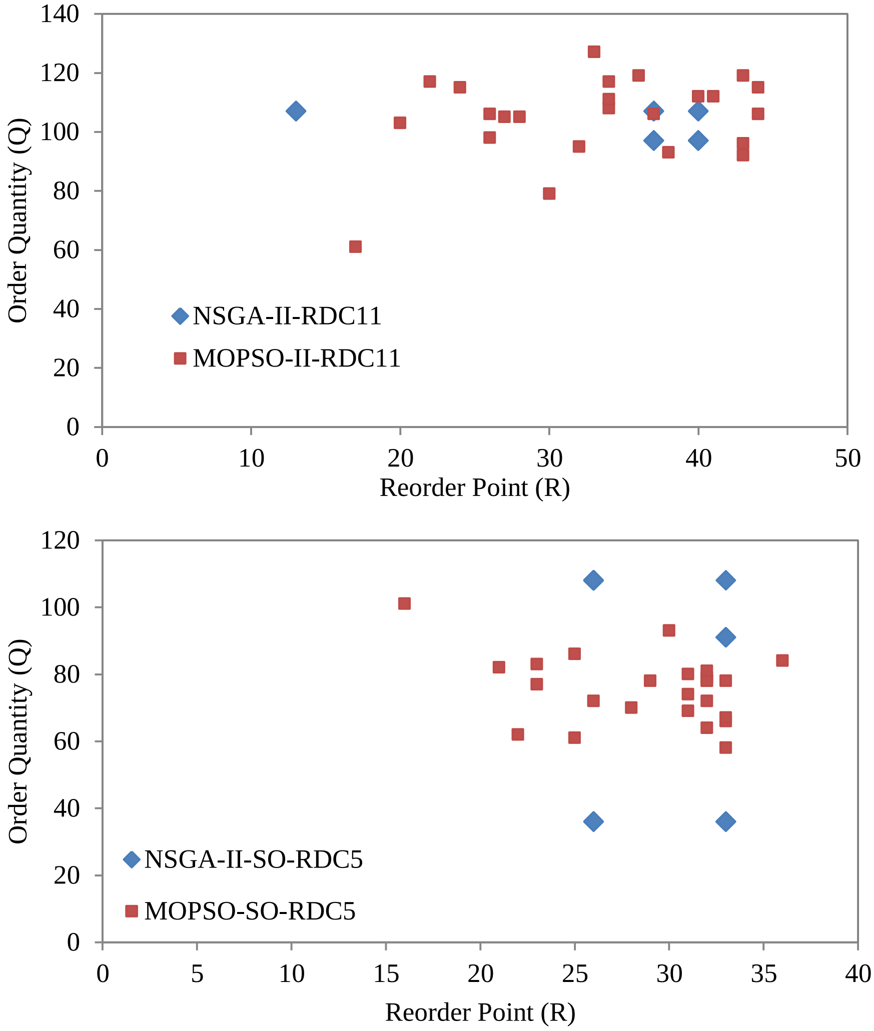


Figure 7-11: The position of non-dominated solutions for RDC5 and RDC 11 in the search space

Many parameters that have great impact on performance and efficiency of the algorithm have to be set for any metaheuristic. In order to see the impact of the population size and the number of generation on the solution quality, the problem with 7 random DCs was chosen as a test case. On the Figure 7-12 the objective function values, obtained during the 20, 50 and 100 runs, are shown. The graphical results show that the MOPSO-SO algorithm performed similarly at small and large numbers of iterations. However, as shown in Figure 7-12, the performance metrics of the Pareto front obtained by 100 generations is better than the solutions obtained by smaller generations in terms of the number of non-dominated solutions, the distance between the members of Pareto front, and the distribution of non-dominated solutions. According to Shi and Eberhart (1999), the performance of standard PSO algorithms is not too sensitive to the population size. However, larger population size in multiobjective optimization problem may be more powerful in exploring the search space and improvement of the quality in the Pareto front (Güller et al., 2015). As it can be seen from Figure 7-13, as the population size grows, the diversity and convergence in the Pareto front obtained by MOPSO-SO also increases.

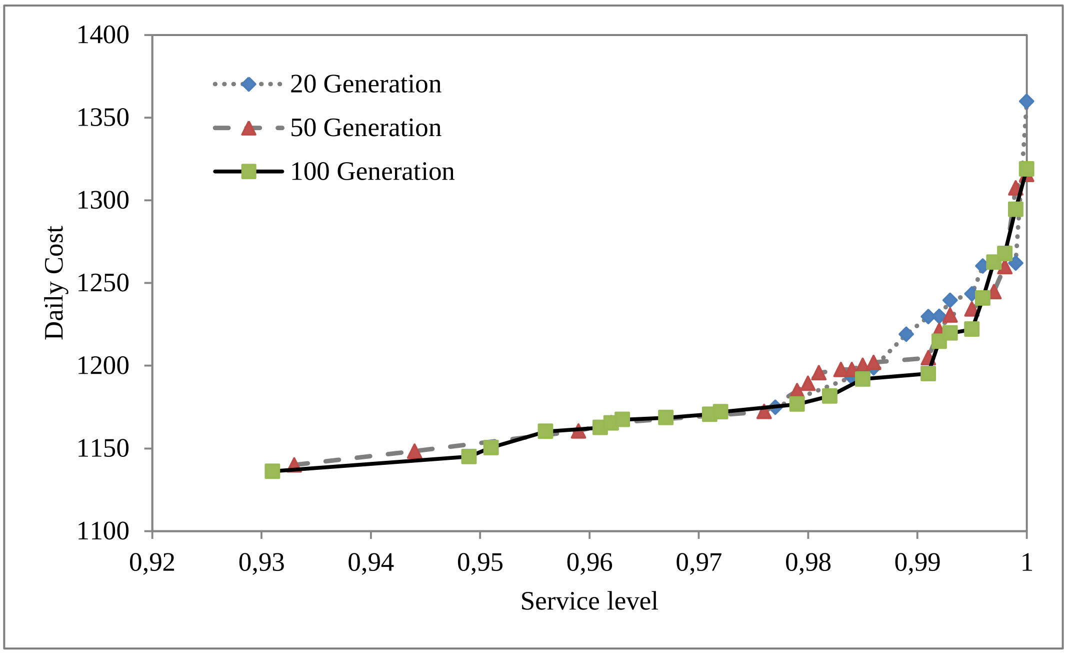


Figure 7-12: Pareto Fronts obtained for different Generation Number

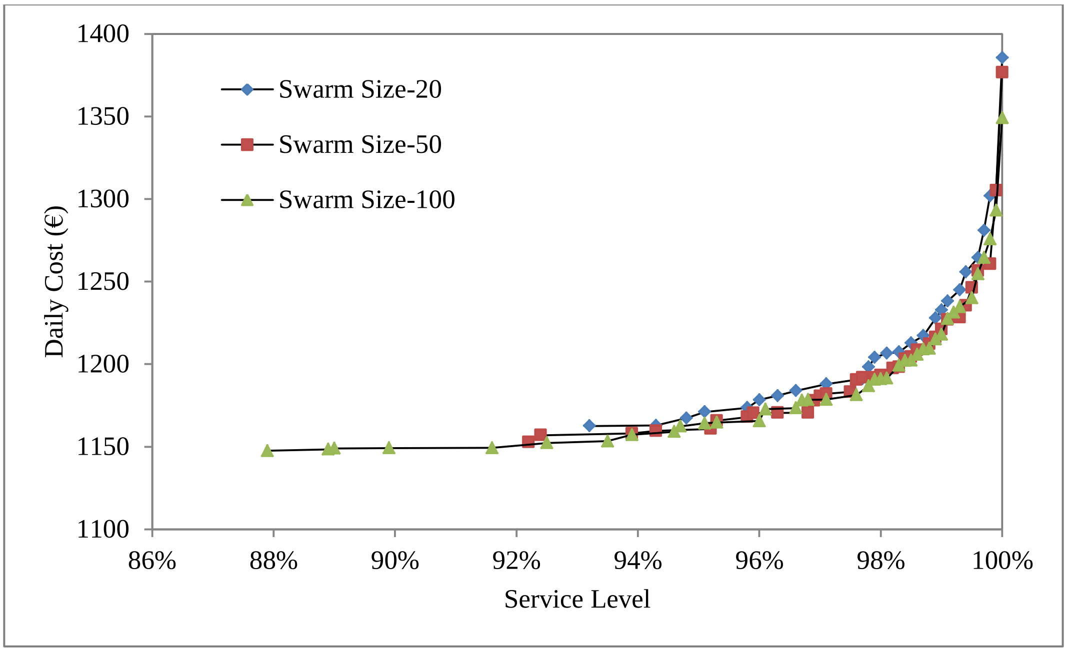


Figure 7-13: Comparison of the Pareto Fronts obtained by different Swarm Sizes

7.5 Summary

In this chapter, simulation-based optimization approach is proposed to determine inventory control parameters in a multi echelon production-inventory system. Two metaheuristics generally applied to a simulation-optimization environment have been discussed, such as multiobjective particle swarm optimization (MOPSO) and multiobjective genetic algorithm (NSGA-II). Previously developed simulation model of multi echelon supply chain comprising customers, retailers, distribution centers, and factories was incorporated into the optimization algorithms to define the optimal inventory parameters for all stock points in a supply chain network. Different experiments were conducted to demonstrate the capabilities of simulation-based optimization model. Furthermore, the capacitated production system contributes to the complexity of lead time between manufacturing sites and local distribution centers. It has been shown that the MOPSO algorithm is a powerful optimization algorithm for multi-echelon inventory system under multiple objectives such as total cost and customer service level. In order to compare the proposed algorithm with commonly used NSGA-II, three performance metrics were considered, such as generational distance, spacing metric, and the number of nondominated solutions. According to the obtained results, the simulation-optimization approach based on MOPSO algorithm is efficient and able to generate a well-distributed set of nondominated solutions with good coverage to optimal Pareto fronts.

Chapter 8

Conclusion and Future Research

This research contributes to two areas. First, it contributes to decision support for supply chain network decisions in an integrated environment. Most literatures on distribution network design have traditionally considered strategic, tactical, and operational decisions separately. This classical approach leads to considerable excess costs because the supply chain is optimized locally but does not guarantee the global optimum for the whole system. Moreover, in real world problems, there are multiple objectives that must be considered simultaneously, but that often have conflicting underlying objectives. This is a challenging problem due to the complexity of the problems, the presence of uncertainty, and the interdependency between decisions. In this research, we discussed how to determine the number and the locations of DCs needed in an integrated supply chain. We formulated a mixed nonlinear mathematical model with objective functions to minimize total logistics costs and minimize the maximum distance from the opened facilities to the customers.

Furthermore, we presented a heuristic based on Quantum-behaved Particle Swarm Optimization (QPSO) to solve the multi-objective location problems in an efficient manner. The solution was tested in the case of a major food product company in Germany. Our results indicate that QPSO can be used effectively to solve multiobjective optimization problems in a relatively simple way. The proposed approach for the multi-objective location problems performs reasonably in terms of computation time. Computational results demonstrate that optimal network structure of an integrated model is quite different from the nonintegrated supply chain. The results suggest that as the ratio between the unit transportation cost and the unit inventory cost decreases, the benefit of integrating the decisions becomes greater.

Another main part of this dissertation is the simulation and optimization of a multi-echelon production/inventory system. We implemented a toolbox developed by using an object-oriented simulation framework. The toolbox is capable of creating simulation models for any kind of supply chain network setting and analyzing the inventory control policies of a given supply chain. The analysis was three fold: i) identified the impact of inventory allocation decisions on the supply chain performance measures under different coordination mechanisms; ii) identified the impact of different order fulfillment strategies on the system performance; and iii) developed the simulation-optimization approach to obtain the best inventory parameters in the supply chain system that satisfy the required service level. We analyzed how the system would behave under different inventory allocation decisions and different order fulfillment policies at the upper echelon. In particular, we noted that FCFS strategy leads to unstable performance among the supply chain. According to the experimental results, customer prioritization polices can reduce the total cost of the system in comparison to FCFS as they increase the customer service level.

In an effort to improve the performance of the multi-echelon supply chain, we presented a multiobjective simulation-based optimization approach in which the cost of all nodes in the system is minimized while the customer service level is maximized. This research presents two metaheuristics algorithms (fast NSGA-II and MOPSO) for dealing with the multiobjective inventory optimization problem. It has been shown that metaheuristic algorithms are powerful, intelligent optimization algorithms that are able to obtain non-dominated solutions of the multiobjective problem. Numerical results for the production/inventory problem with different Pareto optimality characteristics indicate that NSGA-II-SO and MOPSO-SO are capable of efficiently and effectively exploring the solution search space.

8.1 Future Research

The location model in this research has been limited to two objectives: minimizing total logistics costs and minimizing the maximum distance from the opened facilities to the customers. Although these objectives are important for network design, they are not the only important ones. This work did not discuss the sustainable design of supply chain networks given environmental restraints and concerns. An extension of this work could develop an adaptive model for the tradeoff between economic and environmental concerns in decision making framework. Another area for future research is how to improve the performance of the proposed multi-objective QPSO method. This method could improve in several ways. For example, this thesis has assumed that freight transport costs are proportional to the amount of commodities carried. Dismantling this assumption and focusing on optimizing supply chains with variable transportation costs is yet another research topic for exploration.

In this research we consider a system of manufacturers, warehouses, distribution centers, and retail outlets aiming to solve the inventory problem of a multi-echelon supply chain. It would be interesting to relax some of the assumptions to match the real-world scenarios, such as capacity limitations, uncertain costs, raw material availabilities, and inventory allocation policies. Our model assumed a single product with random demand at each customer location. This assumption can be relaxed for multiple products. The simulation system may be extended to the network level with several supplier tiers in order to analyze the impact of the supplier selection process on the inventory system.

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Appendix A

1. Overview of Inventory Theory

One of the main problems of supply chain resource planning is the optimization of lot sizes in order to minimize the costs of ordering and storage.

Classical Lot Size Model (EOQ)

The classic Economic Order Quantity (EOQ) developed by Harris in 1913 is the most fundamental model used to calculate lot sizes. The EOQ model describes an important conflict of costs between fixed ordering and holding costs.

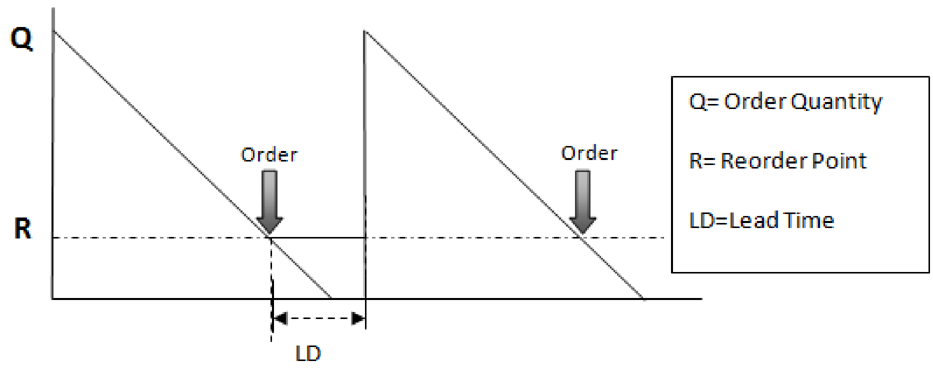


Figure 0-1: Change in inventory over time for the EOQ model

In the EOQ model, since all the parameters are stationary over time, the order quantity, denoted by Q, also remains stationary. The EOQ can be easily determined by the formula:

$$EOQ = \sqrt{\frac{2K\lambda}{h}}$$

where, λ = annual usage

K= fixed ordering (setup) cost

h = inventory carrying cost per unit of product per year

Then, the optimal total cost per year TC* is

$$TC^* = \sqrt{2K\lambda h}$$

Continuous Review Inventory Model

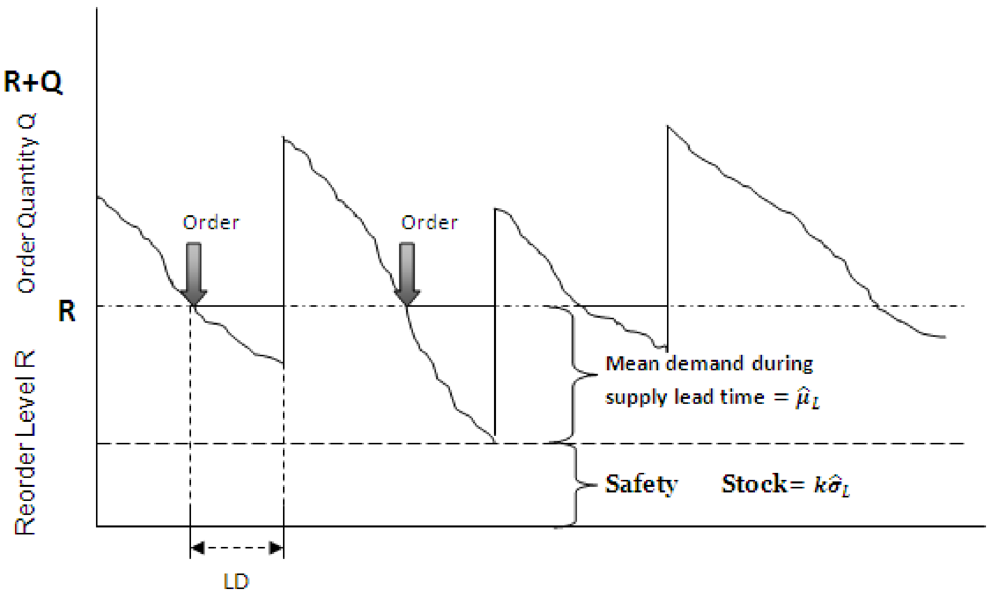


Figure 0-2 Continuous Review Inventory System

EOQ model assume that demand is constant and known. In the majority of cases, though, demand is not constant but varies from day to day. One of the main functions of inventory management is to plan safety stock to protect each stock point uncertainties in customer demands. Considering a single-echelon inventory system with a continuous review control policy, a reorder point of R and batch size of Q, a constant lead time for replenishing orders, demand (per unit time) as a normal distribution with mean μ and standard deviation σ and backordered unsatisfied demand, formulae for the average stock level $D(Q,R)$ and the average stockout level $B(Q,R)$ (see (Axsäter, 2000), (Axsäter, 2006) and (Hadley & Whitin, 1963) for more details):

$$D(Q,R) = \frac{Q}{2} + R - \mu' + B(Q,R)$$

The reorder level consists of two quantities: the first is the average demand during lead time, and the second is the safety stock, which depends on lead time, demand variability, and service level. The expected number of backorders at the location is given by defined as:

$$EB(R) = \int_R^\infty (x-R)f(x)dx = \int_R^\infty xf(x)dx - RH(x)$$

$$= (\mu_L - R)[1-\phi(z)] + \sigma_L\varphi(z) \quad where\ z = \frac{(R-\mu_L)}{\sigma_L}$$

$\mathbf{\Phi(z)}$: is the distribution function of the standardized normal distribution with mean

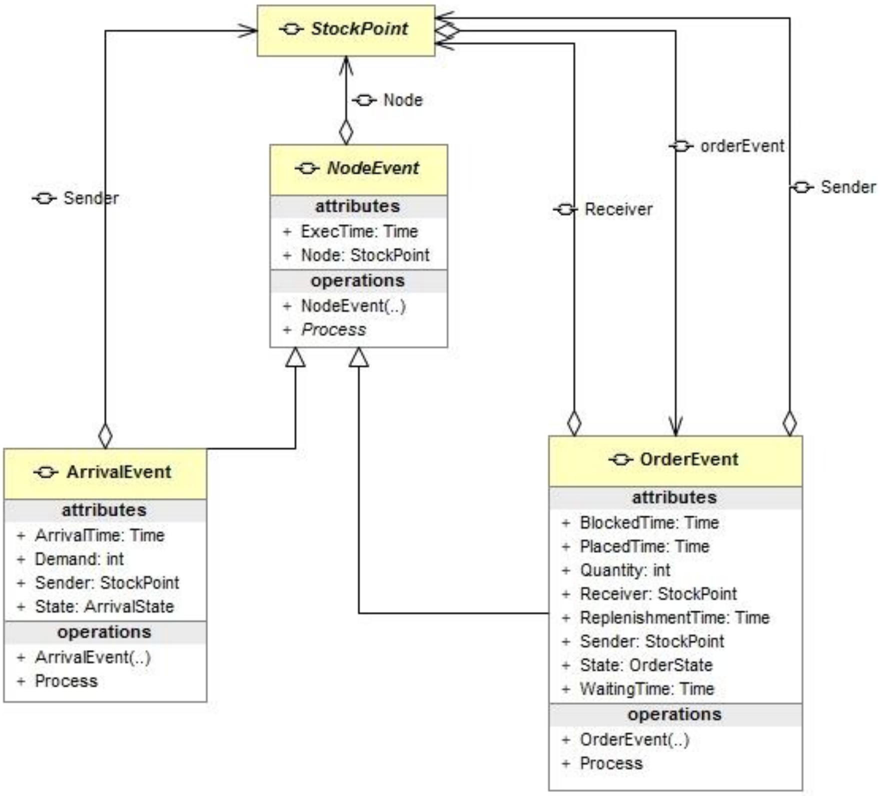
0 and standard deviation 1.

$\boldsymbol{\varphi(z)}$: is the density of the standardized normal distribution.

With last definition, the total cost function can be expressed as follow:

$$C(R,Q) = \frac{AD}{Q} + h\left(\frac{Q}{2} + R - \mu' + B(Q,R)\right) + p\frac{D}{Q}EB(R)$$

Appendix B


StockPoint
Node
NodeEvent
attributes
+ ExecTime: Time
+ Node: StockPoint
operations
+ NodeEvent(..)
+ Process
Sender
orderEvent
Receiver
Sender
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+ ArrivalTime: Time
+ Demand: int
+ Sender: StockPoint
+ State: ArrivalState
operations
+ ArrivalEvent(..)
+ Process
OrderEvent
attributes
+ BlockedTime: Time
+ PlacedTime: Time
+ Quantity: int
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+ State: OrderState
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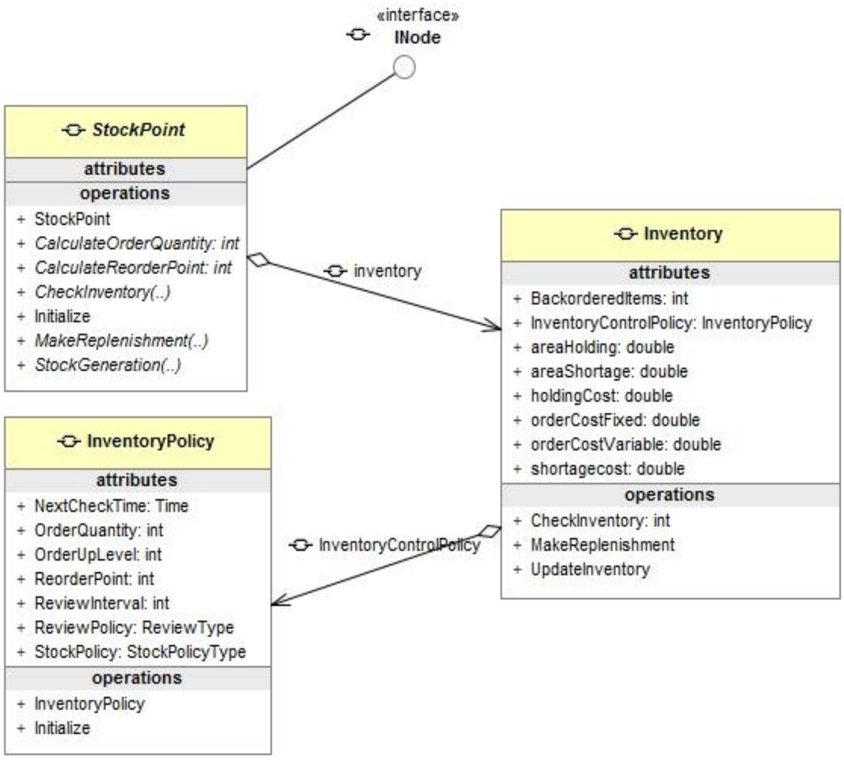
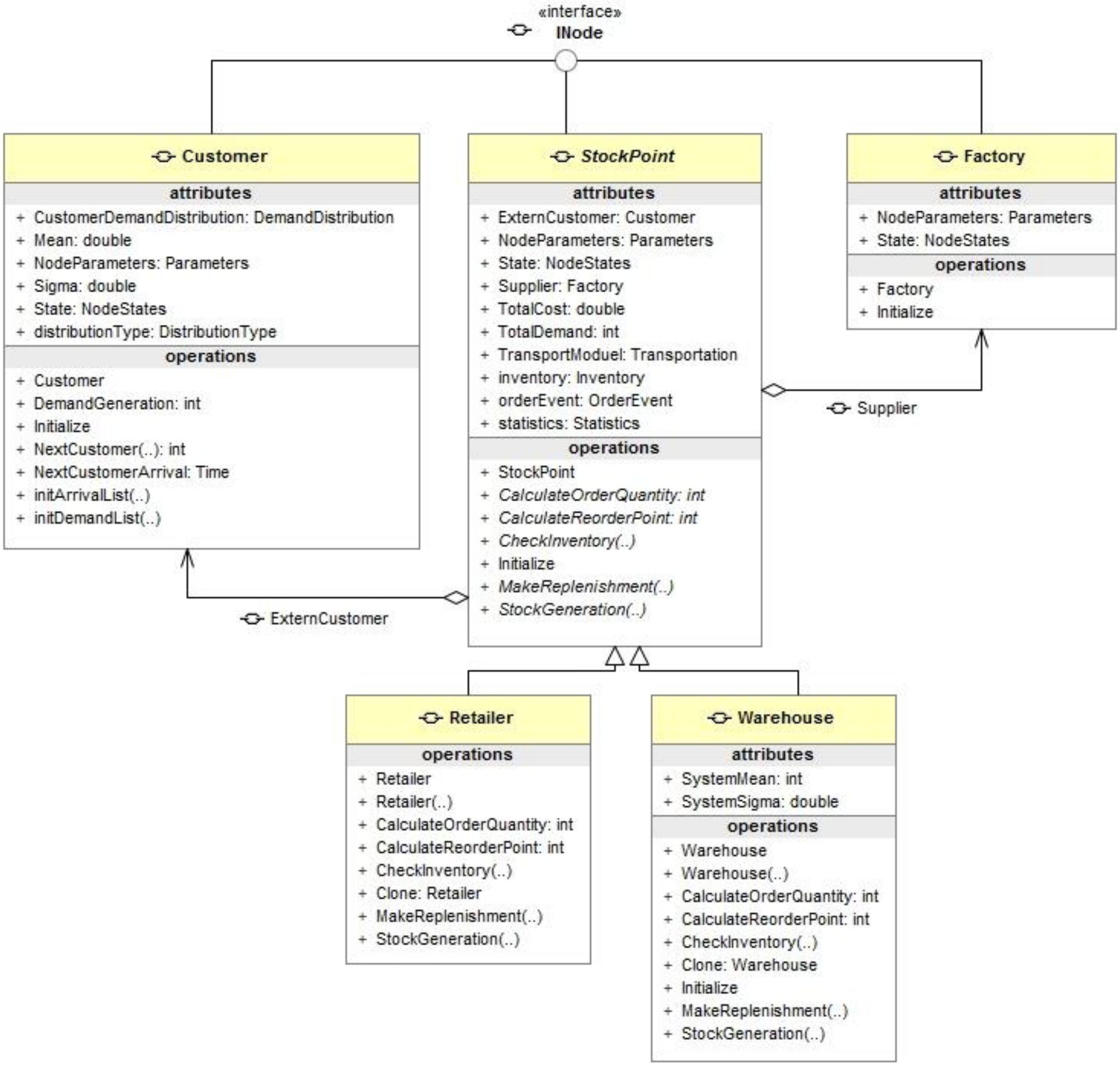
operations
+ OrderEvent(..)
+ Process


«interface»
INode
StockPoint
attributes
operations
+ StockPoint
+ CalculateOrderQuantity: int
+ CalculateReorderPoint: int
+ CheckInventory(..)
+ Initialize
+ MakeReplenishment(..)
+ StockGeneration(..)
inventory
Inventory
attributes
+ BackorderedItems: int
+ InventoryControlPolicy: InventoryPolicy
+ areaHolding: double
+ areaShortage: double
+ holdingCost: double
+ orderCostFixed: double
+ orderCostVariable: double
+ shortagecost: double
operations
+ CheckInventory: int
+ MakeReplenishment
+ UpdateInventory
InventoryPolicy
attributes
+ NextCheckTime: Time
+ OrderQuantity: int
+ OrderUpLevel: int
+ ReorderPoint: int
+ ReviewInterval: int
+ ReviewPolicy: ReviewType
+ StockPolicy: StockPolicyType
operations
+ InventoryPolicy
+ Initialize
InventoryControlPolicy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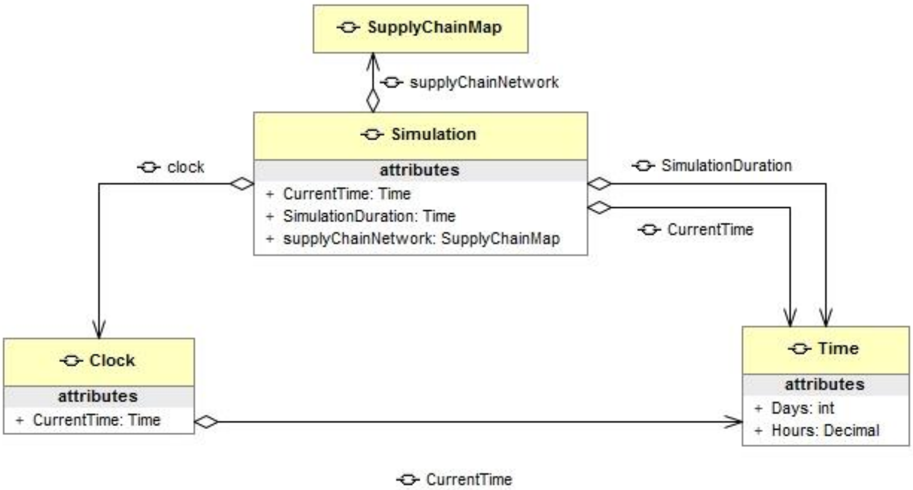
INode
Customer
attributes
+ CustomerDemandDistribution: DemandDistribution
+ Mean: double
+ NodeParameters: Parameters
+ Sigma: double
+ State: NodeStates
+ distributionType: DistributionType
operations
+ Customer
+ DemandGeneration: int
+ Initialize
+ NextCustomer(..): int
+ NextCustomerArrival: Time
+ initArrivalList(..)
+ initDemandList(..)
StockPoint
attributes
+ ExternCustomer: Customer
+ NodeParameters: Parameters
+ State: NodeStates
+ Supplier: Factory
+ TotalCost: double
+ TotalDemand: int
+ TransportModuel: Transportation
+ inventory: Inventory
+ orderEvent: OrderEvent
+ statistics: Statistics
operations
+ StockPoint
+ CalculateOrderQuantity: int
+ CalculateReorderPoint: int
+ CheckInventory(..)
+ Initialize
+ MakeReplenishment(..)
+ StockGeneration(..)
Factory
attributes
+ NodeParameters: Parameters
+ State: NodeStates
operations
+ Factory
+ Initialize
Supplier
ExternCustomer
Retailer
operations
+ Retailer
+ Retailer(..)
+ CalculateOrderQuantity: int
+ CalculateReorderPoint: int
+ CheckInventory(..)
+ Clone: Retailer
+ MakeReplenishment(..)
+ StockGeneration(..)
Warehouse
attributes
+ SystemMean: int
+ SystemSigma: double
operations
+ Warehouse
+ Warehouse(..)
+ CalculateOrderQuantity: int
+ CalculateReorderPoint: int
+ CheckInventory(..)
+ Clone: Warehouse
+ Initialize
+ MakeReplenishment(..)
+ StockGeneration(..)


SupplyChainMap
supplyChainNetwork
Simulation
attributes
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clock
SimulationDuration
CurrentTime
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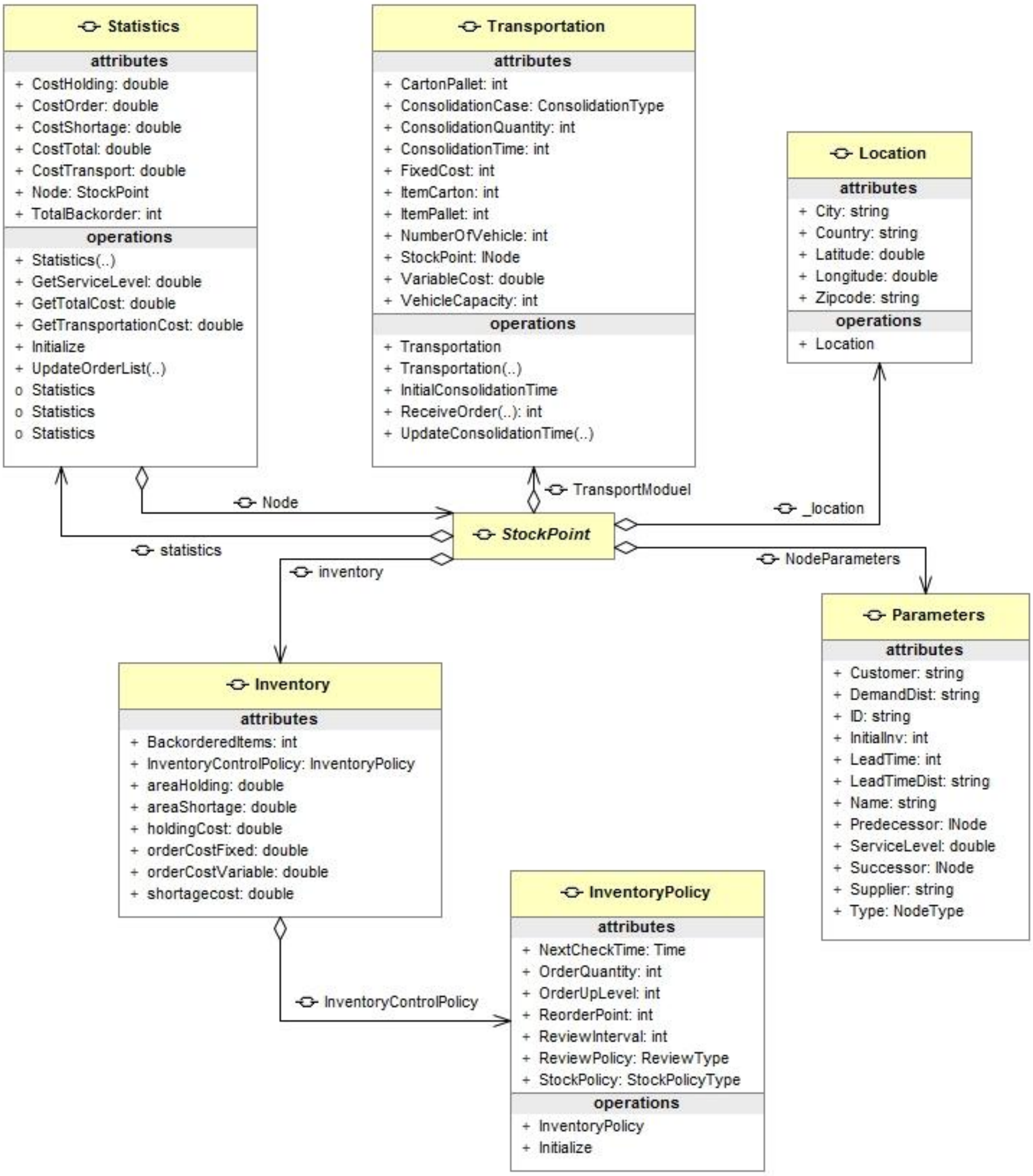
Time
attributes
+ Days: int
+ Hours: Decimal
CurrentTime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attributes
+ CostHolding: double
+ CostOrder: double
+ CostShortage: double
+ CostTotal: double
+ CostTransport: double
+ Node: StockPoint
+ TotalBackorder: int
operations
+ Statistics(..)
+ GetServiceLevel: double
+ GetTotalCost: double
+ GetTransportationCost: double
+ Initialize
+ UpdateOrderList(..)
o Statistics
o Statistics
o Statistics
Transportation
attributes
+ CartonPallet: int
+ ConsolidationCase: ConsolidationType
+ ConsolidationQuantity: int
+ ConsolidationTime: int
+ FixedCost: int
+ ItemCarton: int
+ ItemPallet: int
+ NumberOfVehicle: int
+ StockPoint: INode
+ VariableCost: double
+ VehicleCapacity: int
operations
+ Transportation
+ Transportation(..)
+ InitialConsolidationTime
+ ReceiveOrder(..): int
+ UpdateConsolidationTime(..)
Location
attributes
+ City: string
+ Country: string
+ Latitude: double
+ Longitude: double
+ Zipcode: string
operations
+ Location
TransportModuel
Node
_location
StockPoint
statistics
inventory
NodeParameters
Parameters
attributes
+ Customer: string
+ DemandDist: string
+ ID: string
+ InitialInv: int
+ LeadTime: int
+ LeadTimeDist: string
+ Name: string
+ Predecessor: INode
+ ServiceLevel: double
+ Successor: INode
+ Supplier: string
+ Type: NodeType
Inventory
attributes
+ BackorderedItems: int
+ InventoryControlPolicy: InventoryPolicy
+ areaHolding: double
+ areaShortage: double
+ holdingCost: double
+ orderCostFixed: double
+ orderCostVariable: double
+ shortagecost: double
InventoryControlPolicy
InventoryPolicy
attributes
+ NextCheckTime: Time
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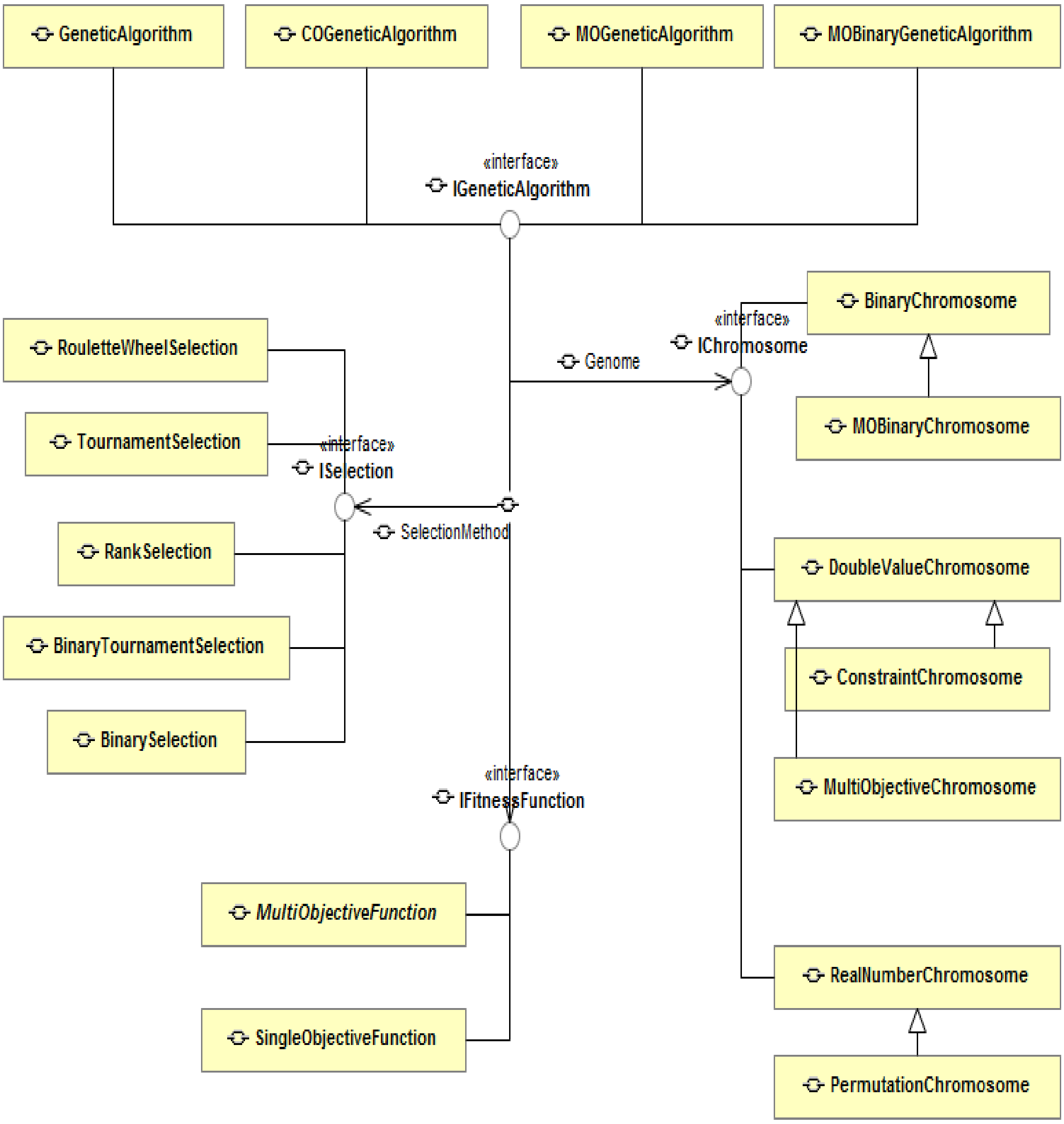
+ ReorderPoint: int
+ ReviewInterval: int
+ ReviewPolicy: ReviewType
+ StockPolicy: StockPolicyType
operations
+ InventoryPolicy
+ Initialize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TournamentSelection
«interface»
ISelection
SelectionMethod
RankSelection
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DoubleValueChromosome
ConstraintChromosome
MultiObjectiveChromosome
«interface»
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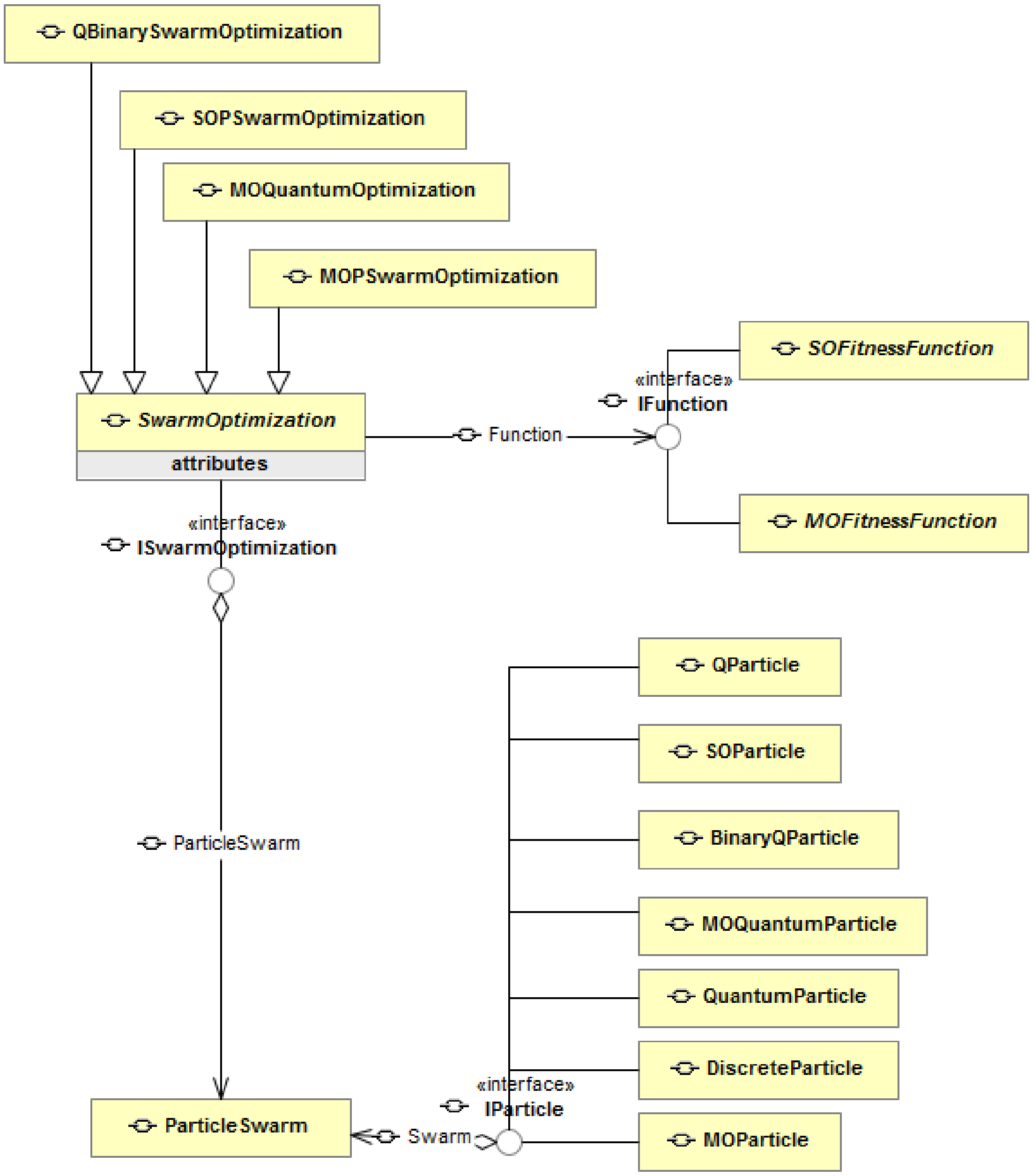
MultiObjectiveFunction
SingleObjectiveFunction
RealNumberChromosome
PermutationChromosome


QBinarySwarmOptimization
SOPSwarmOptimization
MOQuantumOptimization
MOPSwarmOptimization
SOFitnessFunction
«interface»
IFunction
SwarmOptimization
attributes
Function
MOFitnessFunction
«interface»
ISwarmOptimization
QParticle
SOParticle
BinaryQParticle
ParticleSwarm
MOQuantumParticle
QuantumParticle
DiscreteParticle
«interface»
IParticle
ParticleSwarm
Swarm
MOParticle

Appendix C

Average daily demand of regional distribution centers and fitted distribution:

DC	Average Demand (Pallet/per day)	Standard Deviation	CV	Fitted Distribution
RDC-1	13	4	0,31	Erlang
RDC-2	18	10	0,56	Gamma
RDC-3	15	8	0,53	Weibull
RDC-4	13	5	0,38	Normal
RDC-5	16	9	0,56	Normal
RDC-6	20	6	0,30	Gamma
RDC-7	18	6	0,33	Normal
RDC-8	37	20	0,54	Normal
RDC-9	20	9	0,45	LogNormal
RDC-10	17	8	0,47	Normal
RDC-11	20	11	0,55	Gamma
RDC-12	22	12	0,55	LogNormal
RDC-13	25	11	0,44	Gamma
RDC-14	14	6	0,43	Normal
RDC-15	23	10	0,43	Normal
RDC-16	7	3	0,43	Normal
RDC-17	31	16	0,52	Normal
RDC-18	26	14	0,54	Normal
RDC-19	43	18	0,42	Beta

Appendix D

Common parameters for the facility location problem:

μ_i	average daily demand at customer *i*	Uniform [5;20]
σ_i	standard deviation of daily demand at customer *i*	25% of daily demand
f_k	fixed investment cost of locating a distribution center *k*	100 000 € 150 000 € 180 000 €
c_k	variable operating cost of DC *k*	0,5 €/unit 0,3 €/unit 0,2 €/unit
d_{ik}	cost per unit to ship from DC j to customer i, for each $i \in I$ and $k \in K$	0,15 €/km
α	desired percentage of retailers orders satisfied (fill rate)	Type 1 service level = 95%
h	inventory holding cost per unit per day (€/unit-day)	0,01 per unit per day
F_k	fixed cost of placing an order at DC *k* (€/order)	100 €/order
c_{fk}	fixed shipment cost from external supplier to DC *k* (€/truck)	50 €/order
c_{vk}	per unit shipment cost from external supplier to DC *k*	0,15 €/unit
L	Lead time in days	2 days
χ	planning horizon (days in a year)	250