# FORMULATION AND OPTIMIZATION OF A THREE ECHELON MULTI-OBJECTIVE SUPPLY CHAIN NETWORK DESIGN MODEL UNDER SCENARIO BASED UNCERTAINTY

By

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# Declaration

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Md. Mahmudul Hasan

***This work is dedicated to my***
***Loving Parents***

***Md. Nurul Amin***
***and***
***Mrs Shahana Shultana***

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# ABSTRACT

Nowadays, rapid economic changes and competitive pressure in the global market make companies pay more attention on supply chain topics. The company whose supply chain network structure is more appropriate has higher competitive advantage. Propounding the supply chain because of its effect on factors of operational efficiency, such as inventory, response and lead time, specific attention is focused on how to create a distribution network. As nowadays living conditions have changed due to increasing world changes, mutually, situations have changed where supply chains are confronted with and influenced by them. The manager is confronted with more unknown conditions and new risks. Customers' demands have been more uncertain and the lead time on their services is very effective. The demand variety can be recognized as one of the important sources of uncertainty in a supply chain. Moreover, operating cost and capacity of the facilities can also be uncertain those can vary depending on the situations.

This research is presenting a new multi-objective optimization model for supply chain network designs problem. For the first time, a novel mathematical model is presented considering cost and transportation time minimization as well as customer service level maximization under scenario based uncertainty with the existence of several alternatives of vehicles to transport the products between facilities, and routing of vehicles from plants to distribution centers (DCs) and DCs to customer in a stochastic supply chain system, simultaneously. This problem is formulated as a tri-objective mixed-integer linear programming model. The objective of the thesis includes determining the most appropriate transportation channel in terms of choosing suitable vehicles and routes for the second and third echelon of designed supply chain network. All are done in such a way that network wide cost and transportation time are minimized and customer service level are maximized. To solve the model a fast and elitist non-dominated sorting genetic algorithm (NSGA-II) has been used

in Matlab 2013a software after careful analysis of different evolutionary algorithms. This new optimization model is tested on a hypothetical data example, where a multi-stage supply chain design problem is optimized. The results show that the model is presenting the trade-off among different objective functions. Furthermore, the way the model is formulated permits the supply chain to maintain a reasonable higher level of costs, in moments of reducing transportation time and maximizing service level for the customers. Finally, by using the new solving method, the model generated a quality set of Pareto-optimal solutions, which can be used for the decision-maker to evaluate different options for the supply chain network design.

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# Chapter-1

## General Introduction

### 1. Introduction

A supply chain is a set of facilities, supplies, customers, products and methods of controlling Inventory, purchasing, and distribution. The chain links suppliers and customers, beginning with the production of raw material by a supplier, and ending with the consumption of a product by the customer. In a supply chain, the flow of goods between a supplier and a customer passes through several echelons, and each echelon may consist of many facilities.

The ‘‘problem’’ of supply chain network design is very broad and means different things to different enterprises. It generally refers to a strategic activity that will take one or more of the following decisions

- Where to locate new facilities (production, storage, logistics, etc.)?
- Significant changes to existing facilities, e.g. expansion, and contraction or closure.
- Sourcing decisions (what suppliers and supply base to use for each facility).
- Allocation decisions (e.g., what products should be produced at each production facility
- Which markets should be served by which warehouses, etc.

Theoretically SCM is the coordination of transportation, production and inventory Through-out the supply chain in order to deliver the final product to the final client. Supply chain management has also been described as the art of making sure that the right supply is in the right place, at the right time, in the right quantity (at the right cost) anywhere along the chain, all the time. The goal of supply chain management activities is to increase the profitability of the business. This is normally achieved when the company manages to reduce inventory and transportation costs, to increase service level, to limit risks connected to the supply chain (e.g. unmarketable inventory etc.), to gain a vision of the supply chain and tools to control it, or to foresee future changes and to adapt to them.

The supply chain can be defined as an integrated system or network which synchronizes a series of inter-related business processes in order to:

- Acquire raw materials.
- Add value to the raw materials by transforming them into finished/semi-finished goods.
- Distribute these products to distribution centers or sell to retailers or directly to the customers.
- Facilitate the flow of raw materials/finished goods, cash and information among the various partners which include suppliers, manufacturers, retailers, distributors and third-party logistic providers.

Thus the main objective of the supply chain is to maximize the profitability of not just a single entity but rather all the entities taking part in the supply chain. This can only be done if all the entities wish to optimize performance of the supply chain as a whole (system Optimization) and do not place their individual preferences (individual optimization) above that of the system. There must also be complete integration among all the entities so that information can be shared in real-time in order to meet the highly fluctuating demand of the customers. The important issues driving the supply chain and governing its design are:

- Inventory management
- Transportation and logistics
- Facilities location and layout
- Flow of information

Therefore, to maximize the profitability of the entire supply chain it is definitely not enough to optimize these individual drivers separately. Objective functions capturing these drivers have to be optimized simultaneously. Using a goal programming approach to optimization, for each of these individual drivers a tradeoff must be made so as to achieve the main objective or goal which is given the highest priority i.e. there should be no deviation from this goal or this goal has to be achieved irrespective of the other conflicting objectives. It is very obvious that in the above case it is not possible to get a unique solution that satisfies either all the criteria or the objectives because if all the objectives are satisfied then the solution obtained could be a non-Pareto optimal point. Hence we have to find a solution that will come as close as possible to satisfying the other stated goals in the order of preference specified in the goal programming model. Given the nature of the problem and inherent complexity associated with it, it is surprising that very little work has been done in this area. Some of the early attempts to model an integrated supply chain were mostly with single objective functions. Recently researchers have started developing models based on multi-objective functions. These models do not however use an evolutionary algorithm perspective in developing the non-dominated Pareto front.

## 1.2 Rational of the Study

Ensuring competitiveness in today's globally connected marketplace is very demanding and calls for different business strategies than what were employed by businesses in the past. Today's businesses have to be more adaptive to change. In order to stay competitive and continue to subsist they need to be better suited to handle fluctuations in an ever-changing market than their competitors. Production and manufacturing establishments are also faced with such challenges in addition to managing and fine-tuning their supply chains. As described by Hicks, 1999 supply chains can be defined as

"*...real world systems that transform raw materials and resources into end products that are consumed by customers. Supply chains encompass a series of steps that add value through time, place, and material transformation. Each manufacturer or distributor has some subset of the supply chain that it must manage and run profitably and efficiently to survive and grow.*"

From the above definition it is comprehensible that there are many independent entities in a supply chain each of which try to maximize their own inherent objective functions (or interests) in business transactions. Many of their interests will be conflicting. Thus, a specific scenario giving an optimal design configuration using traditional approaches could actually be a non-optimal design of the supply chain when we look at the design from a systems optimization perspective (with respect to a single objective in a two-objective problem). When conflicting interests occur in a problem, modeling the system using traditional optimization techniques (where there exists one weighted objective function) does not commensurate intuitively with a robust formulation. The results could also be misleading in the very likely situation of a dynamic environment. So, the decision maker should ideally be presented with a vector of Pareto-Optimal solutions (also called efficient solutions), and depending on what his/her own intrinsic objective function is with respect to each objective function, he/she can choose the best design from the efficient set of solutions.

The problems of supply-production, production-distribution, and inventory-distribution systems have been studied for many years. Most of these studies focus only on a single component of the overall supply-production-distribution system, such as procurement, production, transportation, or scheduling, although limited progress has been made towards integrating these components in a single supply chain. Supply chain management (SCM) is a subject of increasing interest to academics, and practitioners. SCM can be divided into two levels: strategic and operational. Models have been developed for optimizing supply chain operations at these two levels. The primary objective of strategic optimization models is to determine the most cost-effective location of facilities (plants and distribution centers), flow of goods throughout the supply chain (SC), and assignment of customers to distribution centers (DCs). These types of models do not seek to determine required inventory levels, and customer service levels. The main purpose of the optimization at the operational level is to determine the safety stock for each product at each location, the size and frequency of the product batches that are replenished or assembled, the replenishment transport and production lead times, and the customer service levels. Uncertainty is one of the most challenging but important problems in SC management. Indeed, it is a primary difficulty in the practical analysis of SC performance. In the absence of randomness, the problems of material and product supply are eliminated; all demands, production, and transportation behavior would be completely fixed, and therefore, exactly predictable. In this work we developed a tri-objective model that minimizes system wide costs of the supply chain (fixed cost, variable cost and transportation cost for different vehicles and route), transportation time to shift products to customer zones through particular distribution center and maximize customer service level for a three echelon supply chain. Picking a set of Pareto front for multi-objective optimization problems require robust and efficient methods that can search an entire space. We used evolutionary algorithms to find the set of Pareto fronts which have proved to be effective in finding the entire set of Pareto fronts. This work seeks to integrate strategic and operational analysis of a SC subject to scenario based uncertainty.

## 1.3 Objectives with Specific Aims and Possible Outcomes

The specific objectives of this research are

- To develop a three echelon, multi-product, multi-objectives integrated supply chain network design model (SCNDM) for the joint optimization of cost, transportation time and customer service level.
- To incorporate scenario based uncertainty in the model in terms of three stochastic parameter named by customer demand, operational cost and capacity of the facilities.
- To introduce the selection of transportation channels in terms of choosing the vehicles and routes from available alternatives to minimize the transportation cost and total transportation time for transporting the product from a particular plant to customer zone through a particular distribution center.
- To solve the proposed joint optimization model with the help of a suitable meta-heuristic algorithm for global optimality or searching for pareto optimal solution.

The possible outcomes of the proposed research are mentioned below:

- A supply chain network design model for joint optimization of cost, transportation time and service level will be developed.
- The proposed optimization model will be solved by applying a suitable meta-heuristic or evolutionary algorithm.
- From the obtained pareto font a trade-off will be made for selecting the best solution considering all three objective functions.

## 1.4 Outline of Methodology

The proposed research methodology is outlined below:

- The three objective functions have been developed for minimizing cost and transportation time and maximizing customer service level

- The probability of occurring a certain scenario to incorporate the uncertainty has been assumed due to the unavailability of the data. But, if historical data are available it can be calculated or determined from suitable probability distribution function.
- The different necessary equality and un-equality constraints have been developed to ensure that the proposed model is a bounded one.
- After careful study a suitable meta-heuristic algorithm have been selected to solve the proposed multi-objective optimization model for global optimality by satisfying the constraints already developed.
- Finally, the model has been illustrated and validated with several numerical examples.

## 1.5 Research Design

The progress of the research approach is shown in the figure below. The initial building block is the exploration of Mathematical Programming and Multi-objective optimization fields, in order to define the techniques and methods that should be used for the purpose of this research. Furthermore, the second block describes the proposed model from two points of view, the first one qualitative, and the second one mathematical. At the end, the third building block is including a use case design for the model testing and specific outcomes analysis. In particular, in step 2 a qualitative description of the problem is presented, with all the necessary assumptions, while in 3 the full mathematical formulation for the model design. Moreover, in step 4 an example case is designed and populated with hypothetical data for the purpose of testing the model. Finally, at step 5 the tests are performed, solutions analyzed and specific outcomes provided. However, the exploration of the first block takes part of the research design chapter, while the second and third have dedicated chapters in which details on the model design and testing are presented.

For the goal of the first building block, there is a distinction made between Mathematical Programming and Multi-objective Optimization. The Mathematical Programming is used only as a modeling technique, while the Multi-objective Optimization is addressing the solving methods and generation of Pareto optimal solutions. Thus, for the purpose of the model formulation, Mixed-Integer Programming is identified as the most appropriate technique for modeling facility location and supply chain design problems, since it includes both Yes/No variables for decision making of facility location and continuous ones for managing the flows of materials. The general formulation of both linear and non-linear MIP is presented in order to have a better insight on how models should be built.

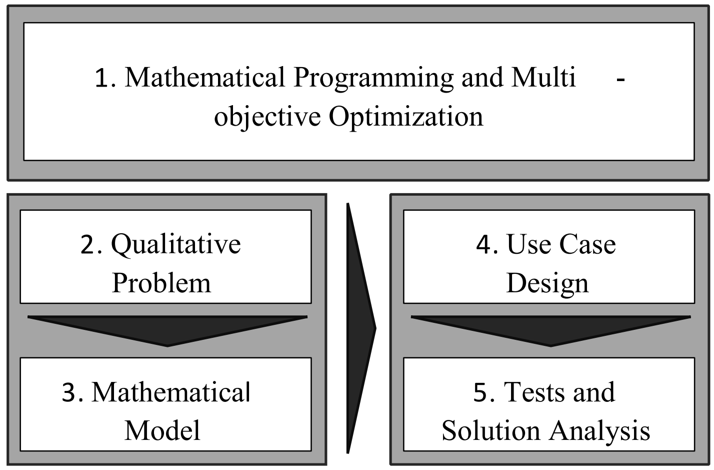



Figure 1: Research Structure

Regarding the Multi-Objective Optimization, a more complete approach is taken, since it is not so obvious which method can be used and which one is better with respect to the others. In particular, the problem of multi-objective optimization is described and the main formulation is presented, where three steps of the optimization process are emphasized: 1) Mathematical Model Formulation 2) Optimization runs and 3) Decision-making process. The first one is addressed with the mathematical programming, while the second and the third are the matter of interest of multi-objective optimization.

For solving multi-objective problems, and generating a set of non-dominated optimal solutions, numerous algorithms and methods are developed. The most diffused ones are implemented in the publications in the thesis' research field, and are being part of the traditional methods. There is a specific analysis dedicated on the formulation, characteristics and usage of the Weighting Method, ε-constrained method and Goal Programming. It is concluded that the methods have major drawbacks in finding a large set of Pareto-optimal solutions; they are sensitive on parameters and settings input, as well as being time costly. The applicability of this kind of methods on a complex model that should address the triple bottom line and generate satisfactory amount of quality solutions, is considered as not favorable option. Therefore, new genetic algorithms are proposed as a solving method. In particular the analysis is between the Multi-objective Genetic Algorithm (MOGA) and the Non-dominated Sorting Genetic Algorithm (NSGA) is conducted.

It is concluded that both of the algorithms are having certain drawbacks, precisely with the sorting procedure and maintaining the variety of unique solutions along the Pareto-optimal frontier. Thus, a new second generation of fast and elitist Non-dominated Sorting Genetic Algorithm NSGA-II is proposed and chosen as a solving method. This type of GA is using an improved fast non-dominated sorting procedure, based on elitism, as well as a new selection operator that permits better allocation of solutions along the Pareto-optimal frontier.

## 1.6 Thesis Outline and Objectives

The aim of this thesis is to perform a research on a new and raising topic of Multi-objective Optimization for Supply Chain Network Design (SCND), to identify the research opportunities, and based on them to propose a new improved model that is addressing the triple bottom line approach in multi-objective optimization in supply chain design. This model should give a better overview on the supply chain performance, and enhance the facility location and design of supply chains network. Nevertheless, its aim is to support the decision-making process by providing quality insights in facility location problems, based on a triple trade-off between cost, transportation time and customer service level of a general supply chain.

In order to structure better the research, this thesis includes four major chapters besides the current Introduction and the final as Conclusion (Figure 6). All of the chapters are having specific organization and topics included, depending on the specific goals set for each of them.

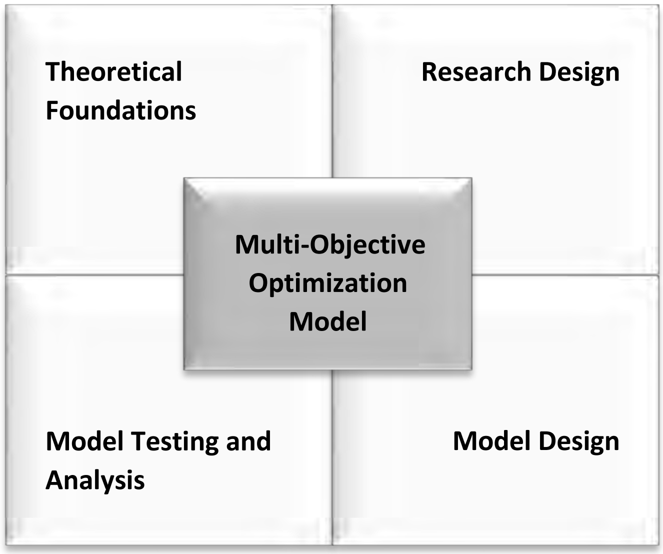



Figure 2: Thesis Outline

The initial chapter on Theoretical Foundations includes three major parts, starting from Supply Chain Management (SCM), moving towards supply chain network design and Facility Location, and finally completing it with the most important part of Literature Review. First, the major concept of SCM is presented with all its major issues and challenges is presented a basic starting point for the topic of supply chains. Furthermore, the chapter gives a comprehensive overlook on Supply Chain Management (SCM), importance of effective and efficient Supply Chain Network Design (SCND) and what are the major concepts including multi-objective optimization and supply chains network design. Before presenting the literature review, a background on facility location problems and production network designs is given, where the main problems in supply chain designs are presented. In this part all the major findings in the topic of interest for the thesis are presented, as well as an important discussion is conducted on the most relevant findings.

The Research Design chapter is a logical continuation on the literature review, where based on the critical analysis and discussion, the research gaps are identified. Thus, the research questions are stated, and objectives defined. For conducting a better research and model formulation, an insight of the most relevant mathematical programming and multi-objective optimization techniques are analyzed. The reason is identification of the right methods for formulating and solving the model

In the Model Design, the new proposed model can be found. Its description and formulation is firstly defined from a qualitative point of view, and afterwards the mathematical design is presented. The qualitative description is defining the supply chain problem, the eco-system of the supply chain and the necessary assumptions that are structuring the problem. Based on the qualitative definition, a new MILP model for multi-objective optimization for supply chain network designs is presented. It can be seen in a complete formulation and description of the mathematical model. Moreover, there are special parts dedicated to the novelties embedded by the model, where a definition and explanation of their functionality is presented.

The last chapter, before the conclusion of the thesis, is dedicated to the model testing and results' analysis. The first part is dedicated to the testing example, explaining its structure, main characteristics and data population. Furthermore, the tests performed on the model are presented, where it can be found a section related to each of the three research questions specifically. Out of the results' analysis, specific conclusions and outcomes are identified. The main goal and structure of this chapter is focused on assessing the functionality of the model and analysis of the outcomes regarding the trade-offs based on the triple bottom line approach.

# Chapter-2

## Theoretical Foundations

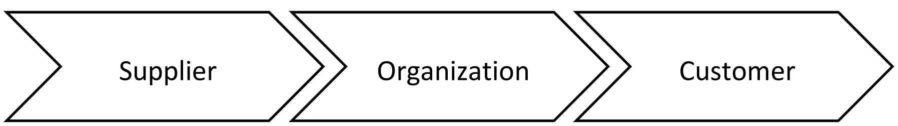
In the following chapter, the theoretical background of the literature research is explained. In order to have a better overview of the foundations, several broader concepts that are important for the research presented. Having these concepts explained, in can be passed towards the core literature review. Thus, the theoretical foundations include:

1. **Supply Chain Management (SCM)**
2. **Facility Location and Production Network Design**
3. **Literature Review on Optimization Models for Supply Chain Network Design (SCND)**

The first point of the theoretical foundations should give a quick overview on what is supply chain management, why it is important, and what are the main aspect encompassing. After having a basic idea on SCM, the idea of sustainability in SCM can be presented. Here it moves towards the scope of the thesis, and by explaining the major concepts of sustainability, the basis for the last two components of the foundations is set. Hence, explaining the facility location problem and supply chain network design is the last topic that should be covered in order to have a comprehensive picture, before entering the core literature review part. The last point of the theoretical background is a crucial aspect for the research, where a specific approach is followed in order to structure and analyze the literature. Having that, the main research gaps can be identified, and form the research questions that should be answered in the following chapters.

## 2.1 Supply Chain Management (SCM)

Supply Chain Management is a relatively new research stream in the past 20 years, and it is an ever growing research topic. Since the globalization of the companies and the supply chains contributed for more complex operations and network structures, the need of SCM has emerged. In order to introduce the concept of supply chain management, first, what supply chain is has to be understood. According to Mentzer, supply chain is "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer". It can be constituted of production and distribution facilities of a focal company, suppliers' facilities and customers (Figure 3). Supply chain is focused on the focal organization activities, without any integrations inside the supply chain. An integration is a step further that organizes the materials, production, and physical distribution activities.




` Figure 3: Supply Chain Elements

SCM goes beyond the logistics processes and the internal integration of a supply chain of a single supplier, organization and customer. It can be defined as "the task of integrating organizational units along a supply chain and coordinating materials, information and financial flows in order to fulfil customer demands with the aim of improving competitiveness of the supply chain as a whole. From the definition, it can be seen that some aspects as coordination, information and financial flows, as well as competitiveness, are complementary with the definition of supply chain (Figure 4).

The goal of SCM is to integrate and coordinate all the components of the supply chain in an efficient and effective way in order to make the supply chain competitive, with a final goal of being focused on the customer requirements. There are several aspects of the SCM that are critical, which can be presented by the house of SCM (Figure 5).

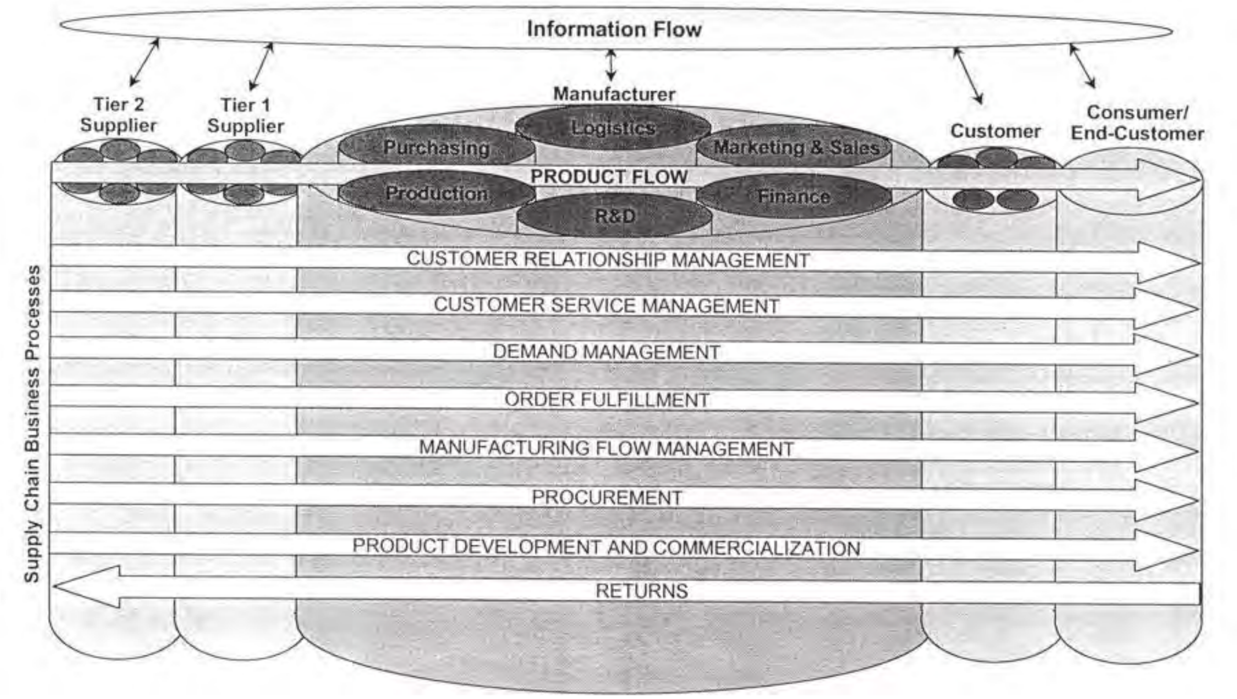



Figure 4: Supply Chain Management

SCM is driven by the 1) integration and 2) cooperation between the various entities inside the supply chain, which makes them the two most important pillars that can guarantee good 3) customer service, and long-term 4) competitiveness.

### 2.1.1 Integration of Supply Chains

The integration in SCM has to interlink all the internal processes of the company with the partners in the supply chain. The emerging new enterprise network of companies, partners, processes and technologies, are creating the need of integration, relationships, and inter-dependences. In order to achieve integration, we have: 1) Leadership, 2) Network Organization, and 3) Partners, as the three main aspects that are leveraging integration.

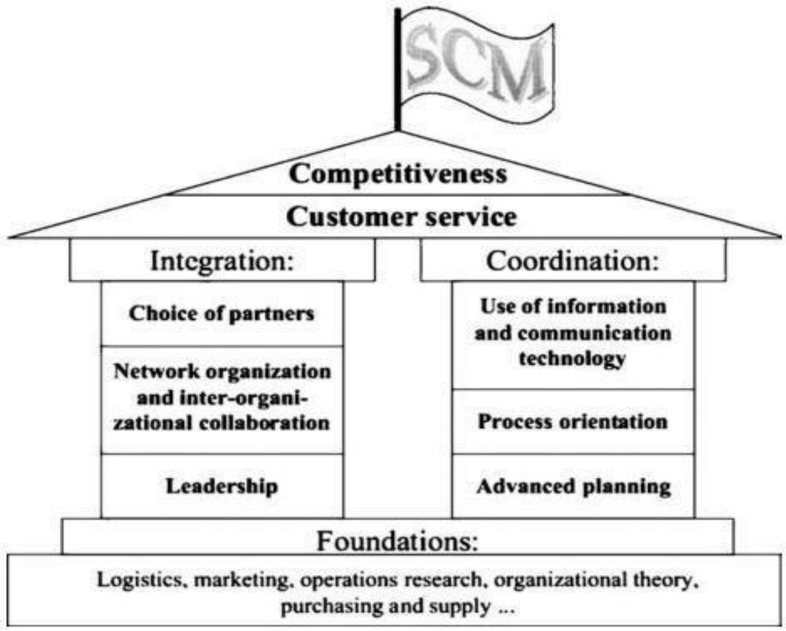



Figure 5: House of SCM

1. **Leadership**

A supply chain can have two extremes, having one company as the ultimate powerful leader, or having all the entities with equally divided powers. In-between we can search different possibilities of integration, and organization. However, the goal of leadership is to have one part of the SCM dedicated on integration and developments of the supply chain. As for any strategic movement, the integration needs leadership and vision.

2. **Network organization and inter-organizational collaboration**

Are crucial for one supply chain. Big importance is given on the network organization, because nowadays the relationship with suppliers is critical for success. Moreover, all of the companies are part of global supply chains, and commonly part of more than one, which makes the problem of network organization more complex. At the same time, there must be an existing attention on the collaboration inside the company, since those processes are influenced from the network, but what is more important they are influencing the network. In total, network organization is a complex problem, which is unavoidable aspect of supply chain's functioning. Managing the relationships between different entities is not a trivial task, and needs attention.

3. **The choice of partner**

   For organizing the network and designing the structure of the network itself. Finding good partners, which are best fitting the supply chain, is a long term goal. While performing this task, it is crucial to understand the already established and potential relationships of partners in various supply chains. Having this information, a right decision can be made for the choice of partners.

### 2.1.2 Coordination in Supply Chains

The coordination has to enable endless flows of material, information and financial flows. Everything should be organized in a coordinated way, in order to have better efficiency in the business processes. Time is a key performance indicator in supply chain performance, therefore proper coordination is crucial for lowering the lead times and improving the performance. As enablers of coordination, we have 1) Process Orientation, 2) Information and Communication Technology, and 3) Advance Planning Systems.

1. **Business processes**

   Business processes are one of the building segments of SCM (Figure 2). In order to have efficient supply chains, there is a constant need of re-engineering and improvements of the processes. An important issue here is the link between the processes in the overall supply chain. Since the supply chains are tending to become more complex, and to integrate the processes of different partners, the links between are requiring special attention. There is a need of analyzing and improving the links in order to avoid inefficiencies such as process redundancy.

2. **Information and communication technology**

   Information and communication technology can have a huge impact on the efficient and effective exchange of information between partners. It can integrate many entities, and can enable fast and up-to-date information flow. Moreover, it can be an enabler not just of coordination, but as well as collaboration by data sharing between the partners, such as demand forecast and production plans.

3. **Advanced Planning Systems (APS)**

Advanced planning systems are based on the principles of hierarchical planning and make extensive use of solution approaches known as mathematical programming and meta-heuristics. These systems include decision supporting analysis and information that are used in the planning phase of the SCM, and are aiming at filling the gap of the ERP (Enterprise Resource Planning) systems. APS are including planning activities on short-term, mid-term and long-term periods, starting from strategic network planning, going towards master and demand planning, and at the end managing activities such a production and transportation planning on operational levels (Figure 6).

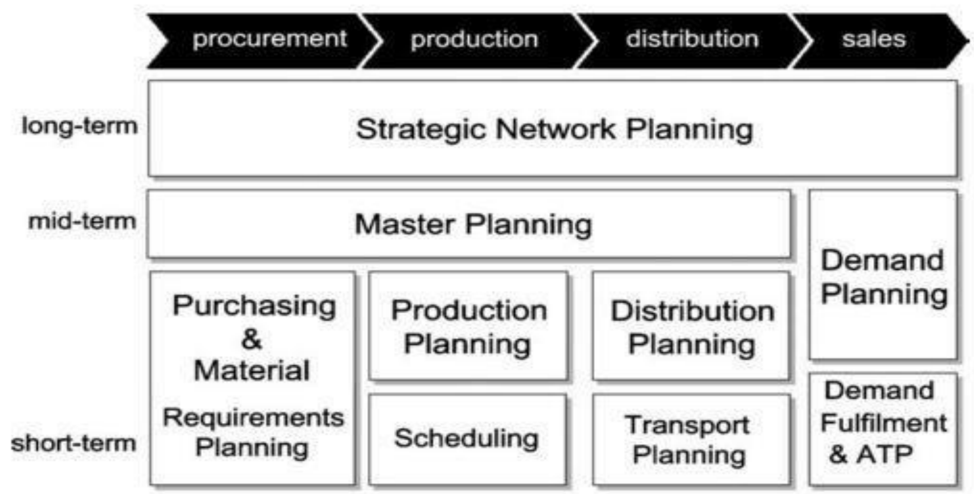



Figure 6: Software Modules Covering the Supply Chain Planning Matrix

### 2.1.3 Customer Service and Competitiveness

In order to have a competitive supply chain, the customer service should be excellent. A good customer service brings value to the supply chain and enables sustainable competitive position. The roof of the house of SCM should be a constant goal of the SCM, and all the integrative and coordinative actions should aim at achieving better levels of customer service. The pillars and their components are having the role of enablers, on which the supply chain performance is leveraging.

## 2.2 Covering Problems

While a $P$-median problem is focused on the average weighted distance travelled, the covering problems are using the maximum accepted travel distance. Thus, these problems are dealing with covering a certain area within a maximum acceptable travel distance or time. A good example are the everyday milk runs done by lorry trucks in the grocery business, which must serve a certain area for a limited time. There are two main ways of attacking this problem. The first one is called Location Set Covering, and aiming at minimizing the cost of facility location for a specified level of coverage. At this problem, the number of demand nodes and demand amount do not influence the results, since all the nodes within the level of coverage should be served. This can give an idea to the decision maker how much can it cost a certain level of coverage, or in other words, how many facilities are needed in order to cover the service area. The risk of unfeasibility is however present in this kind of modeling.

The second problem is called Maximal Covering problem, and aims at maximizing the demand covered in the maximal distance or time, by locating a limited number of facilities. This problem aims at resolving the potential infeasibility that can emerge from the investment constraints on the needed facility locations.

1. **Set Covering Problem** as an integer linear program:

| ***Inputs*** |
|---|
| $C_j$ – fixed cost of locating facility at node $j$<br>$S$ – maximum acceptable service level distance/time<br>$H_i$– set of facility sites $j$ within acceptable distance of node $i$ |
| ***Problem formulation*** |
| $Minimize \sum_{j} C_j Y_{ij}$ (7)<br>$Subject\ to: \sum_{j \in H_i} X_j \geq 1 \quad \forall i,$ (8)<br>$X_j \in [0,1] \quad \forall j.$ (9) |

Objective function (7) minimizes the cost of facility location, or by having the cost of one facility, we can assume it as minimizing the number of facilities located. Constraint (8) assures that at least one facility is located for every demand, within the acceptable service level. Constraint (9) is setting the binary variable.

2. **Maximal Covering Problem** as an integer linear program, and a new decision variable introduced:

| ***Decision variables*** |
|---|
| *$Z_i$ – 1 if a node I is covered, 0 otherwise* |
| ***Problem formulation*** |
| $Minimize \sum_j d_i Z_i$ (10) |
| $Subject\ to: Z_i \leq \sum_{j \in H_i} X_j \quad \forall i,$ (11) |
| $\sum_j X_j \leq F \quad \forall j$ (12) |
| $X_j \in [0,1] \quad \forall j,$ (13) |
| $Z_i \in [0,1] \quad \forall i.$ (14) |

Objective function (10) is maximizing the covered demand. Constraint (11) determines the covered demand nodes in an acceptable service distance. Constraint (12) sets the limit on potential facility locations. Constraints (13) and (14) are integrality constraints.

### 2.2.1 Dynamic Location Problems

Even though the previous discussed problems are the basic research topics, and are the most used ones, the real world problems are not so deterministic and static. All the problems in SCM and SCND require models that are tackling uncertainties. The time span of a strategic decision regarding the strategic planning of SCND is set further in the future, which means the uncertainty is significant. Moreover, having the fact that SCND is a big investment for a company, adopting decision-making based on deterministic problems is accumulating more risk. Dynamic location problems are dealing with implementing future uncertainties into models. There are recognized two types of problems, Dynamic Single Facility Location Problems and Dynamic Multiple Facility Location Problems.

### 2.2.2 Stochastic Location Problems

While the Dynamic Location Problems are having fixed input parameters in the models, and dealing only with the uncertainty of the future events, Stochastic Location Problems are dealing also with the uncertainty of the inputs. The idea is to have a probabilistic approach that will include the unpredictable nature of supply chains and have SCND decisions based on a more realistic data. Based on the approach, there are two different ways of addressing stochastic problems, with Probabilistic or Scenario Planning models

The Probabilistic models are capturing the stochastic aspect of facility location trough explicit consideration of the probability distributions associated with modeled random quantities. In such models, we can have modeling of the supply and demand uncertainty, capacity shortages and capacity availability, distribution uncertainty, etc. Under these types of problems are included also the Queuing Models, based on the queuing theory, and are tackling facility location problems with a specific approach.

The approach that is followed in Scenario models is based on several possible future outcomes. These kind of stochastic problems are trying to tackle problems of uncertainty by evaluating future scenarios. Scenarios can be qualitative or quantitative description of future circumstances, which can help the decision making process in taking into considerations future changes. Based on these predictions, several types of solutions can be evaluated depending on the risk willing to take, and scenarios that want to be addressed in decisions.

### 2.2.3 Multi-objective Problems (MOP)

As a final part of the facility location and SCND design problems, an introduction in multi-objective problems is presented. Since the focus on this research is multi-objective optimization, these problems are described here briefly, and furthermore, in Chapter 3 details on multi-criteria decision-making and multi-objective optimization will tackle in details this topic. MOP can be both deterministic and stochastic. They should be considered as a different type of more complex and complete SCND problems.

Multi-objective problems, as already mentioned before, are trying to model and solve SCND problems with more than one objective. These objectives can be both minimizing or maximizing ones, and usually conflicting between each other. A good problem of this type is defined by more than one objective function, set of constrains, and a technique for obtaining solutions. Since there is an existing trade-off between the objectives of the problem, there should not be one unique solution, but on the contrary a set of non-dominated solutions. This set of solutions means that none of the objectives can be improved, without compromising another one. Usually a trade-off between the objectives is present. Therefore, there must be higher decision-making criteria that will choose a preferred solution from the set. There are different types of solving techniques that are able to provide a good set of the so-called Pareto optimal solutions, which are based on some traditional approaches, or on evolutionary algorithms.

The problems that can be addressed here, are existing in a significant number, such as minimizing different types of cost, transportation distances, time for traveling, lost sales, investments, or maximizing profit, customer satisfaction, quality assurance. However, current trends are moving towards sustainability not just from a financial point of view, but also from an environmental and social one. Sustainable Supply Chain Network Design recognizes that the long-term competitive advantage should be achieved through the alignment of economic, social and environmental goals.

## 2.3 Literature review

The supply chain (SC) has been viewed as a network of facilities that performs the procurement of raw material, transformation of raw material to intermediate and end products, and distribution of finished products to retailers or directly to customers. These facilities, which usually belong to different companies, consist of production plants, distribution centers, and end-product stockpiles. They are integrated in such a way that a change in any one of them affects the performance of others. Substantial work has been done in the field of optimal SC control. Various

SC strategies and different aspects of SC management have been investigated in the literature. However, most of the developed models study only isolated parts of the SC.

Structuring a global supply chain is a complex decision making process. The complexity arises from the need to integrate several decisions each of which with a relevant contribution to the performance of the whole system. In such problems, the typical input includes a set of markets, a set of products to be manufactured and/or distributed, demand forecasts for the different markets and some information about future conditions (e.g. production and transportation costs). Making use of the above information, companies must decide where facilities (e.g. plants, distribution centers) should be set operating, how to allocate procurement/production activities to the different facilities, and how to plan the transportation of products through the supply chain network in order to satisfy customer demands. Often, the objective considered is the minimization of the costs for building and operating the network.

Historically, researchers have focused relatively early on the design of production/distribution systems [10]. Typically, discrete facility location models were proposed which possibly included some additional features but that still had a limited scope and were not able to deal with many realistic supply chain requirements. However, in the last decade, much research has been done to progressively develop more comprehensive (but tractable) models that can better capture the essence of many supply chain network design (SCND) problems and become a useful tool in the decision making process. This can be seen in the papers by Melo [1-2] where it also becomes clear that many aspects of practical relevance in supply chain management (SCM) are still far from being fully integrated in the models existing in the literature.

As pointed out by Shapiro [3], in corporate planning, financial decisions may strongly interact with the supply chain planning. In fact, structuring and managing a supply chain is often just part of a whole set of activities associated with a company. Accordingly, the investments in the supply chain must be integrated with other profitable investments. Typically, several points in time can be considered, in which the investments can be made or in which their return can occur (which in turn, may allow further investments in the supply chain). Additionally, due to the large capital often associated with the network design decisions, the possibility of taking advantage of some investment opportunity is often considered, which justifies the use of loans.

In addition to the financial aspects just mentioned, the multi- period nature of some decisions has often to be accommodated in SCND models. Usually, a supply chain network has to be in use for some time during which the underlying conditions may change. In some situations, a single-period facility location model may be enough to find a ‘‘robust’’ network design. However, in most cases, it is possible and even desirable to allow a change in the decisions in order to better absorb the changes in the parameters and thus to adjust the system accordingly. Location decisions are often among such decisions. In such cases, typically, there is a discrete set of points in time in which changes can be made in the network structure. These points allow a partition of the planning horizon into several time periods and constitute the initial setting for a multi-period network design problem. As pointed out by Melo [4]

Another feature that can hardly be avoided in many SCND problems regards the uncertainty associated to the future conditions which may influence the input of the problem, and the need to include this uncertainty in the models supporting the decision making process. Different sources of uncertainty exist that can be included in the models [5] such as demand, production or distribution costs, supply of raw materials, etc. The uncertainty existing in these data leads to the need to find robust SCND decisions and/or consider ways for measuring and optimizing the risk associated with those decisions.

A constraint often considered in the literature devoted to SCND problems is that all the demand must be supplied throughout the planning horizon. However, for several reasons such constraint may become meaningless. Firstly, because demand is uncertain. Secondly, because due to the existence of other investments in alternative to those that can be made in the supply chain, the company may find it better not to invest in a supply chain the amount needed to assure the complete demand satisfaction. Finally, it may simply be a marketing strategy not to supply all the demand in some time horizon. Taking these arguments into consideration, a more interesting and from a practical point of view more reasonable alternative is to measure the service level (e.g. the proportion of satisfied demand) and to reward it in the objective function.

The features that we consider in the new modeling framework have been considered in the literature although, to the best of the author's knowledge, their integration was never attempted. Two of such features which are unavoidable in SCND regard the multi-period, multi-commodity nature of many realistic problems. As it has been noticed by Melo [6] such features have been addressed in the literature but mostly in a deterministic setting. Fleischmann et al. [7] Consider a problem in which the decisions to be made regard location, distribution, capacity, production and investment. The objective is to optimize the net present value. In the problem studied by Hugo and Pistikopoulos [8] the decisions involve location, distribution and capacity of the facilities. Two objectives are considered: the net present value (to maximize) and the potential environmental impact (to minimize). Ulstein [9] Consider the location of a single echelon of facilities. The decisions also involve the flow of commodities through the network and the capacity of the facilities. A profit maximization objective is considered. Canel [10] consider a SCND problem and search for the best location for a set of intermediate facilities in a two-layer network as well as for the best way for shipping the commodities through the network. Hinojosa [11-12] Consider two location layers with location decisions to be made for both layers. In the first paper, location and shipment decisions are considered. The second paper considers, in addition, inventory and procurement decisions. Finally, Melo [1] Consider a generic number of echelons with the possibility of making location decisions in all layers. Production, distribution, procurement, capacity and investment decisions are also considered.

The inclusion of uncertainty issues in SCND problems in general and in facility location models in particular is not new and has been addressed by many authors [13]. Nevertheless, as pointed out by Melo [14], the scope of the models that have been proposed is still rather limited due to the natural complexity of many stochastic optimization problems. In particular, most of the literature considers single-period single-commodity problems. Nevertheless, several papers can be found addressing multi-commodity problems in a single-period context. This is the case with the problems studied by Guille´n [15], Listes- and Dekker [16], Sabri and Beamon [17] and Santoso [18]. These authors consider two to multiple echelons. The decisions concern the flow of commodities, capacities, production or procurement and inventory decisions. Stochasticity is assumed for demand, production costs and delivery costs, respectively and the objectives concern the profit, the net revenue, the costs, the demand satisfaction or just the flexibility (regarding the volume or delivery).

The combination of multi-period decisions with a stochastic setting is proposed by Aghezzaf [19] although considering only a single commodity. Two facility layers are considered with location decisions being made for just one of them. In addition to the location decisions, distribution, inventory and capacity decisions are also considered. Stochasticity is assumed for the demands. A robust optimization approach is proposed for the problem. The same type of approach was also proposed by Pan and Nagi [20] who considered a multiple layer supply chain network. Demand is assumed to be uncertain. Distribution, production and inventory decisions are considered in addition to the decision of where to locate the facilities.

As mentioned above, the possibility of not satisfying all the demand makes sense in many SCND problems. This possibility has been modeled by a few authors. Sabri and Beamon [17] consider the service level as one objective function to maximize in a bi-objective optimization problem. Hwang [21] considers a single-commodity SCND problem with two facility layers. Location as well as routing decisions are considered. Stochasticity is associated with traveling time (assumed to have a known distribution). A minimum service level is imposed in terms of the number of facilities to establish. The goal is to assure a minimum probability for a customer to be covered which is expressed as a function of the distance and the travel time between the facilities and the customers. The objective is to minimize the number of facilities established. Miranda and Garrido [22] propose a sequential heuristic approach to optimize inventory service levels in a two-stage supply chain. A single-period single commodity setting is considered.

Most literature models only consider single criterion for the supply chain planning and optimization, such as cost [23-24], profit [25-26] and net present value (NPV) [27-28]. One of the earliest papers using multi-objective method for supply chain [29] proposed a multiobjective approach for vendor selection, considering three objectives including the purchases cost, number of late deliveries, and rejected units.

The inclusion of risk management in SCND problems has been addressed in the literature although in rather limited settings. Lowe Measure the risk associated with exchange rates fluctuation. A single-commodity, single-echelon problem is considered. Despite the inclusion of several multi-period factors involved in the problem, the location decisions are static. In addition to these decisions, production, procurement and capacity of the facility decisions are also part of the decision making process. A two-phase multi-screening approach is proposed taking into account several cost factors. Goh et al. [30] consider a single commodity, single-period, single-layer facility location problem. Stochasticity is assumed for the demand and for the exchange rates. Several risks are considered namely those related with supply, demand, exchange, and disruption. Two objectives are handled: profit maximization and risk minimization. El-Sayed [31] address a single-period multi-commodity supply chain network design problem. Uncertainty is assumed for the demand. In addition to the location of the facilities, it is necessary to make a decision about distribution, production and inventory.

The inclusion of uncertainty in supply chain management problems leads often to the need to consider stochastic programming approaches. Not many papers exist with such approaches for SCND problems although a few can be referred. In Schutz [32-33] and Listes [16] two-stage stochastic programming formulations are considered. Alonso-Ayuso et al. [34] present a two-stage stochastic programming model for multi-period single-commodity supply chain planning problem. Uncertainty is assumed for product net price, demand, raw material supply and production costs. No location decisions are made but it is possible to make decisions regarding the capacity of the facilities which can change throughout supply chain decisions in addition to the typical location–allocation decisions.

In the recent literature many optimization approaches and algorithms have been developed and proposed in order to solve several problems in the field of logistics and transportation. Ribau [35] utilised Genetic Algorithm (GA) to optimise the official driving cycle for a hydrogen powered fuel cell hybrid bus. Ma [36] proposed a mixed integer linear programming method to optimise the lane markings. In [37] GA-based optimized hierarchical fuzzy rule-based system was proposed to predict the traffic congestion in [38], a GA based graph model developed for alternative traffic restriction problem. Bhattacharya [39] proposed a kernel support vector mechanism based traffic flow estimation model to determine the states of the road traffic flow to generate an optimized schedule using a mixed integer programming.

Considering that there is no single algorithm which can find the best solution for all types of optimization problems according to the no-free lunch theorem [40], in literature, several models have been proposed to solve supply chain design problems to get the Pareto optimal solutions. Most of these models are based on genetic algorithm and its enhanced versions [41-42]. In addition to the genetic algorithm-based supply chain models, several other methods have also been proposed especially based on the swarm-based optimization methods [43-45]. A swarm-based optimization model is proposed for a resource options selection problem in a bulldozer supply chain design in [46]. The model is based on Ant Colony optimization technique to solve the multi-objective problem and to find the Pareto solution set where the aim is to find best combination of the resource options by minimizing the total cost and the total lead-time. The same resource options selection problem has been solved by Mastrocinque [47] Proposing a multi-objective optimization based on the Bees Algorithm [48]. The proposed approach showed encouraging results for solving the supply chain configuration problem.

There has been a growing interest of using evolutionary algorithms to solve multi-objective optimization problems recently [49-51]. Different models have been developed with different objective functions where evolutionary algorithms have been used to find Pareto fronts. Sabri and Beamon [17] developed an integrated multi-objective supply chain model for strategic and operational under certainties of products-delivery and demands. Similarly Melachrinoudis *et al.*[52] worked on a bi-objective optimization with cost minimization and service level maximization as objectives. Pinto [50] and Altiparmak [53] independently proposed a solution procedure based on genetic algorithms to find the Pareto optimal solutions for supply chain design problem.

Farahani and Elahipanah [51] set up a bi-objective model for the distribution network of a supply chain which produces one product in a three echelon supply chain design. The objectives were: minimizing costs and minimizing backorders and surpluses of products. The Pareto optimal were found by using mixed integer programming by applying non-dominated sorting genetic algorithms.

Most of the existing models places much emphasis on the optimization of location and allocation decisions while ignoring important aspects such as capacities and technology aspects of the manufacturing facilities which also affects the production and distribution of products. In addition, many models have been implemented using genetic algorithms, genetic algorithms in particular. It should be noted that with large size problems they take long run time to find optimal solutions and sometimes they may converge towards a limited region of the Pareto fronts ignoring solutions that might be interesting. In such cases, there is need to guide the algorithm to converge towards desirable solutions if prior information is available.

One of the important factors of the total productivity and profitability of a supply chain is to consider its distribution network, which can be used to achieve variety of the supply chain objectives. Designing a distribution network consists of three sub-problems, namely, location allocation, vehicle routing, and inventory control. In the literature, there are some research studies amalgamating two of the above subproblems, such as location-routing problems, inventory-routing problems, and location inventory problems. These three sub-problems of a distribution network design are considered in few papers simultaneously. Location-routing problems are surveyed and classified by Min [54] and Nagy and Salhi [55]. Inventory-routing problems are studied in several studies Zhao [56], Yu [57], Oppen and Loketangen [58]. In addition, a number of studies have considered location-inventory problems [59]. Finally, Ahmadi Javid and Azad [60] presented a new model for a location routing-inventory problem. They considered one objective for their model and did not consider transportation time and risk- pooling.

One characteristic that differentiates the problem introduced by Olivares-Benitez [61] from previous works in the literature is the study of the tradeoff between lead time and cost in the supply chain design, related to transportation choices. The review by Current [62] makes evident that the balance of these criteria had not been studied extensively. After that, Arntzen [63] addressed the supply chain design problem for a company that handled the cost-time tradeoff as a weighted combination in the objective function. The decision variable was the quantity of product to be sent through each transportation mode available. Transportation time was variable with respect to the quantity shipped. The problem was solved using elastic penalties for violating constraints, and a row-factorization technique. Zeng [64] emphasized the importance of the lead time cost tradeoff, associated to the transportation modes available between pairs of nodes in the network. A mixed-integer programming model was proposed to design the supply chain optimizing both objectives. In this work facility location was not addressed. The method proposed was a dynamic programming algorithm to construct the efficient frontier assuming the discretization of time. In the model proposed by Graves and Willems [65] cost and time were combined in the objective function. The supply chain was configured selecting alternatives at each stage of the production and distribution network. A dynamic programming algorithm was used to solve this problem.

In recent years multi-objective problems in supply chain design have been treated with more emphasis taking advantage of increased computational resources and new methods. Chan [66] presented a multi-objective model that optimized a combined objective function with weights. Some of the criteria included cost and time functions, and one of the components of time was transportation time. Transportation time varied linearly with the quantity transported. The model included stochastic components, but facility location was not considered. A genetic algorithm was the base of an iterative method where scenarios with changing weights were solved.

Altiparmak [53] proposed a model with three objective functions to minimize total cost, to maximize total customer demand satisfied, and to minimize the unused capacity of distribution centers. Here, transportation time was handled as a constraint that determined a set of feasible distribution centers able to deliver the product to the customer before a due date. They proposed a procedure based on a genetic algorithm to obtain a set of non-dominated solutions. In the work by El Maraghy and Majety [67] a model was proposed to optimize cost, including the cost of late delivery. The model considered the dynamic nature of the decisions. They used commercial optimization software to solve the model, analyzing different scenarios. The review by Farahani [68] about multi-criteria models for facility location problems describes some works where metrics of cost and service level are considered. The metaheuristic methods mentioned include multi-objective versions of Scatter Search, Tabu Search, Simulated Annealing, Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO).

However, some other metaheuristics that were created for multi-objective applications were also mentioned, like Simple Evolutionary Algorithm for Multi-objective Optimization (SEAMO), Strength Pareto Evolutionary Algorithm version 2 (SPEA2), Pareto Envelop based Selection Algorithm (PESA), Non-dominated Sorting Genetic Algorithm II (NSGA-II), Vector Evaluated Genetic Algorithm (VEGA), and the Multi-Objective Genetic Algorithm ( MOGA ).

More recently, several works have appeared for multi-objective supply chain design. Pishvaee [69] studied a model for a forward/reverse logistics network design from a bi-objective optimization perspective. The objectives to optimize were the total cost of the system and the fulfillment of the demand and return rates. Although they considered lead time into their model, similar to Altiparmak et al. [53] it was considered in the meeting of a due date, and not related to transportation alternatives. They developed a memetic algorithm to solve this NPhard problem. Moncayo-Martinez and Zhang [70] proposed a model similar to that of Graves and Willems [65] where activities must be selected to design the supply chain. This was a bi-objective model that optimized cost and lead time in a multiechelon network. The decision variable is the selection of the resource for a certain activity in the supply chain. They used a Pareto Ant Colony Optimization metaheuristic to obtain the Pareto Optimal Set. Liao [71] also studied a multi-objective problem for supply chain design. In this case they integrated location and inventory decisions. The objectives were the minimization of cost, the maximization of the fill rate, and the maximization of demand fulfilled within a coverage distance. The lead time was implied in the cost of the safety stock, but it was not related to transportation decisions. The method proposed was a hybrid of NSGA-II and an assignment heuristic. Pinto-Varela [72] presented a bi-objective optimization model for the design of supply chains considering economic and environmental criteria. In their model, time was considered since the point of view of a multi-period approach. Different transportation modes may exist, but they are not associated to the time. They solved three small examples with mathematical programming commercial software. The review by Mansouri [73] emphasized the importance of multi-objective optimization techniques as decision support tool in supply chain management. Although order promising decisions and network design decisions were identified as important criteria, none of the works reviewed integrated them in a multi-objective approach. Chaabane [74] presented a multi-period multi-objective optimization problem where cost and environmental objectives were optimized. In their mixed-integer programming model, the selection of transportation modes was considered as a decision variable but it was not connected with time. They used mathematical programming commercial software to solve small instances of the problem. Sadjady and Davoudpour [75] studied a problem for supply chain design where cost and time were tied to transportation alternatives. The approach, however, was to optimize a single objective function where lead time from the transportation alternative was transformed into a cost function. The cost objective function is optimized using a Lagrangian relaxation method. As proposed by Olivares-Benitez et al. [61] the cost and time criteria may not be comparable and should be treated in separate objectives.

It is important to highlight some works that solve real cases for supply chain design. Altiparmak et al.[53] applied their genetic algorithm for a supply chain design for plastic products in Turkey. Pati [76] solved a case for the Indian paper recycling industry. Sousa [77] applied their models for the design of an agrochemicals supply chain. Gumus [78] solved the case for a company in the alcohol free beverage sector. Moncayo-Martinez and Zhang [70] applied a Pareto Ant Colony Optimization metaheuristic to design a supply chain for Bulldozer production. Pinto-Varela [72] presented a bi-objective model for designing supply chains in Portugal. Chaabane [74] solved a case for aluminum production. Funaki [79] proposed a very complete model and a dynamic programming algorithm to design a supply chain for a machinery product. Marvin [80] formulated a mixed integer linear programming problem to design a supply chain for ethanol biorefining. Paksoy [81] applied fuzzy optimization for the design of a vegetable oil supply chain. These works illustrate an increasing interest in the application of supply chain design models in industry.

It is interesting to note the review by Griffis [82] where they presented the use of metaheuristics in logistics and supply chain management from year 1991 to 2012. Near 15% of the applications were in the area of supply chain design. They highlight the use of Simulated Annealing and Tabu Search among local search metaheuristics, with minor attention in the literature to greedy randomized adaptive search procedure (GRASP), variable neighborhood search (VNS) and others. In terms of population search techniques, the most popular have been Genetic Algorithms and Ant Colony Optimization, with fewer mentions for Scatter Search, Particle Swarm Optimization, and others. However in this review it is evident the few applications of multiobjective metaheuristics, especially for supply chain design problems.

The research described above shows that few works considered the cost-time tradeoff derived from the transportation channel selection in the supply chain design. Other differences with the problem addressed in this research are explained in the following lines. First, in some works the transportation time is a linear function of the quantity transported. In the model presented here, a single time is used for each arc between nodes, which represents more real conditions in the operation of transportation. Second, in many studies the time-cost tradeoff has been addressed from a single objective perspective transforming the time in a cost function. Here, the time and cost are treated as separate criteria allowing for the construction of sets of non-dominated solutions. This approach may be a good choice when the preference of the decision maker for one of the objectives is not known, or when the criteria cannot be compared easily. Third, in many multi-objective problems for supply chain design, the cost-time tradeoff was not associated to the selection of the transportation channel. In the problem addressed here, the selection of transportation from several alternatives has a direct impact in the lead time objective. The combination of these elements and traditional supply chain design decisions makes relevant the problem addressed, and the necessity to solve it.

Manufacturing industry companies operate a wide variety of assets, widely varying ages and expected lifetimes. At any given time, the decisions relating to investment in infrastructure include how best to configure assets at existing sites and whether to establish new sites. These are tied in with production and inventory planning. The main issue associated with investment planning is that capacity-related decisions have impacts far beyond the time period over which confidence in data exists. Hence, decisions must be made in the face of significant uncertainty relating in particular to the economic circumstances that will prevail in the future. Uncertainty may be caused by external factors, such as demand, prices, availability of production resources, etc. or internal ones like promotion of new products, improvement of product quality, etc. Demand uncertainty has been early recognized in the supply chain management context as the essential cause of the ‘‘bullwhip effect’’, which is characterized by excess volatility in demand. In order to capture terms of uncertainty in design and operation of supply chain networks, two mathematical formulations have been developed: (a) scenarios or multi-period approaches and (b) probabilistic approaches.

SCM models under demand uncertainty have received significant attention in the literature. The body of literature related to these models is extensive. Our review of the literature is indicative and not exhaustive. Interested readers could refer to the excellent reviews of: (a) Snyder [5] regarding approaches for optimization under uncertainty applied in facility location problems regarding systematic consideration of uncertainty within supply chain optimization problems for the process industries.

Tsiakis [23] show how demand uncertainty can be introduced in a single-period steady-state model. They argue that future uncertainties can be captured well through a scenario tree, where each scenario represents a different discrete future outcome. These should correspond to significant future events rather than just minor variations in demand. They utilize a multipurpose production model where flexible production capacity is to be allocated between different products, and determine the optimal layout and flow allocations of the distribution network.

Al-Othman et al. [83] presented a multi-period optimization model framework for the optimal design of petroleum supply chains under uncertainty in both product demands and prices. They concluded that the design of supply chains in such uncertain and unstable economic environments is characterized by high levels of danger and risk, since many unpredictable factors can be appeared.

Pan and Nagi [20] considered the design of a supply chain for a new market opportunity with uncertain customer demands. A robust optimization model was proposed where expected total costs, cost variability due to demand uncertainty, and expected penalty for demand unmet were the three components in the objective function. In this model uncertainty was captured via scenario approach while the objective was to choose one partner for each echelon and simultaneously decide for each partner the production plan, inventory level, and backorder amount.

You and Grossmann [28] presented a mixed-integer optimization approach for the optimal design of responsive supply chains in the present of demand uncertainty. A multi-period mixed-integer nonlinear programming model was developed for the maximization of net present value and minimization of expected lead time. Chen and Lee [84] presented a mixed-integer nonlinear programming problem for the design and operation of supply chain under multiple objectives and uncertain product demand.

You and Grossmann [28] presented a mixed-integer nonlinear programming (MINLP) model that determined the optimal network structure, transportation, and inventory levels of multi-echelon supply chain under customer demand uncertainty. The initial MINLP model was reformulated as a separable concave minimization program and a spatial decomposition algorithm was introduced in order to obtain near global optimal solutions. The applicability of the model was illustrated via two supply chain examples and the results were discussed and analyzed.

## 2.4 Identification of Key Findings and Research Gaps

By performing a critical analysis on the structured literature, it was able to identify the key findings in the current research field. Furthermore, comparing the researching streams between authors led towards identification of the research gaps and definition of the thesis' research direction.

The most recent comprehensive review for facility location and supply chain management demonstrated that most of the literature deals with deterministic models when compared with stochastic ones (approximately 82% against 18%) [14]. Uncertainty is one of the most challenging but important problems in the practical analysis of SCND performance. However, the literature in the background of SCND under uncertainty is still scarce. Because of the difficulty in solving stochastic SCND problems, research on more complex multi-echelon models under uncertainty has only begun to appear in the literature in the past decade. Many of these models may be viewed as stochastic extensions of the seminal model by Geoffrion and Graves [85]. Although, the majority of papers in the literature on integrated SCND problems are for the deterministic environment, recent research in SCND problems under uncertainty is increasing significantly.

However, the most important fact is, though the aim of achieving minimum cost throughout the network and ensuring maximum customer satisfaction level within minimum transportation time are highly correlated, very few works represent the joint consideration of these three. This gap of the existing literature inspires the author of this work to come up with a multi-objectives, multi-echelon, multi product SCND model under stochastic conditions with the consideration of minimizing cost (fixed cost, variable cost and transportation cost) and transportation time along with the maximization of customer service level when different alternatives of vehicles and routes are available.

# Chapter-3

## Research Design

In the previous Chapter of Theoretical Foundations, a literature review is performed, where all the publications relevant for the research topic are analyzed. Out of the analysis, several discussions are triggered as new possible research streams. These discussions are the so far identified gaps in the research field considering multi-objective optimization for supply chain network designs (SCND).

### 3.1 Research Structure

After the literature review is conducted and the research gaps identified, the research questions are stated. Based on the research questions, the research objective are set, and based on these previous steps, further sections are aiming at fulfilling the gaps by answering the issues raised. For that reason, the research is structured in three building blocks (Figure 25), where the first one is part of this chapter, while the other two have the following chapters specifically.

1. The first step of the first building block has the aim of explaining what is mathematical programming and multi-objective optimization, as well as the relevant approaches that are included in this research field. The focus is on the model configurations for a supply chain design, and the algorithms that can be used for obtaining an optimal set of solutions.

2. In the qualitative problem description can be seen the explanation of the problem that is a part of this research, its main characteristics and objectives. In particular, the supply chain design problem that is a focus of the research is presented, with the main

decisions that the problem should provide. Moreover, the necessary assumptions for giving a well structure problem are presented.

3. According to the qualitative description, the mathematical formulation of the model is presented, where all the necessary elements are explained. The mathematical model design is the core part of the research, where the objective functions, decision variables, parameters, and constrains are defined. Setting the decision variables in a proper way in the objective functions, while constraining the model in a proper way, as well as giving the right input parameters, are the issues that are part of the model formulation.

4. For proper testing of the functionality of the new proposed model, a specific case study is designed. In particular, a supply chain structure is presented, described by various nodes and arcs connecting them. Moreover, the case study is populated with the necessary data for all input parameters.

5. At the end, the tests are performed using the case study's data, where various solutions are analyzed. This stage aims directly towards answering the research questions and assessing the performance of the model. Furthermore, out of these tests, future improvements of the model can be identified.

### 3.1.1 Mathematical Programming and Multi-objective Optimization

Mathematical Programming, Mathematical Optimization, Multi-objective optimization, Pareto Optimization, Multi-objective Programming are some of the many terms existing in the Operations Research that are dealing with building mathematical models for addressing and optimizing various problem. There has not been made so far a clear distinction between the terms according to the focus they have and problems that they address. However, for the purpose of this research Mathematical Programming is referred as a single objective optimization, where a minimizing or maximizing problems can exist for assessing the best alternative from a set of alternatives. On the other hand, Multi-objective optimization is referred to problems with more than one objective, usually conflicting, where several possible alternatives can be assessed.

In order to optimize a multi-objective problem, there are three necessary steps that should be done always, 1) Mathematical Model Formulation, 2) Optimization runs, and 3) Decision-making. The mathematical model formulation is dealing with the construction of the problem by formulating it in a mathematical form, where all the decision variables, parameters, objective functions and constraints are defined, and the mathematical relations structuring the problem. The step of optimization runs is the actual solving of the model with a proper algorithm, where various solutions are provided. These solutions at the end have to be evaluated by the decision maker and according to the preferences to select the most preferable solutions.

Therefore, at the first step of a multi-objective optimization, for the purpose of this research, mathematical programming is used. Namely, the Mixed-Integer Linear and Non-linear Programming as the most diffused and appropriate for designing supply chains. MILP and MINLP are techniques for setting up mathematical formulations in supply chains, which are widely used for addressing facility location problems, production decisions and allocation problems, as well as routing and transportation problems. However, mathematical programming is a vide field, where different subfields are existing besides mixed integer programming. Some of them are linear and non-linear programming, stochastic programming, quadratic programming, dynamic programming etc. Although, all of these techniques can be used for optimization of various problems, all of them are addressing single-objective objective function problems. Furthermore, this research is not interested in using these techniques as solving algorithms, but just as modeling methods which are helping the formulation of the mathematical models.

### 3.1.2 Multi-objective Optimization

Multi-objective Optimization is a field of research under the branch of a broader field called Multi-criteria Decision Making (MDCM), where at least two conflicting objective functions are formulating an optimization problem. It is more and more clear in the world that there is no such as single objective problems, where just the costs should be minimized, or the quality can be improved, without affecting other performance indicators. Moreover, in terms of sustainability there are several possible trade-offs between the objectives determined by the triple bottom line. Therefore, as discussed before, a multiobjective optimization process needs a mathematical formulation, a solving algorithm and a decision making process. These three necessary elements can be a part of different optimization problems, where different steps are followed, but at the end of an optimization process, the mathematical model should obtain a set of solutions by using a certain algorithm, from which the decision maker can assess the most suitable ones. These optimal solutions, in the field of multi-objective optimization are called Pareto optimal or Pareto-efficient solutions. For the purpose of this research, the expression Pareto-optimal is used for defining a set of solutions from a multi-objective optimization.

Pareto-optimal solutions are a result of an optimization process of at least two conflicting objective functions, where various solutions can be obtained, without preferences on which one is better. This set of solutions are called non-dominated solutions, since without a higher-criteria from the decision-maker, it cannot be said which one is the most optimal one. A general formulation of a multi-objective optimization problem for obtaining a Pareto-optimal set of non-dominated solutions can be defined as:

$$Minimize \quad \{f_1(x), f_2(x), \ldots, f_k(x)\} \tag{17}$$

$$Subject\ to: x \in S \tag{18}$$

The multi-objective formulation is evolving $K \geq 2$ conflicting objective functions $f: R^n \rightarrow R$, that need to be minimized. Usually an optimization model is formulated by minimizing objective functions, but having maximization is also present and possible. The other characteristics of an multi-objective model are:

- The set of decision variable vectors of $= (x_{1,2}, \ldots, x_n)^T$ belong to the nonempty feasible region of $S \subset R^n$.

- Objective vectors are set as images of the decision vectors and consist of objective function values $z = (x) = (f_1(x), f_2(x), \ldots, f_k(x))^T$. These objective vectors are forming the objective feasible region of $Z = (S)$.
- An objective vector is evaluated as an optimal solution only if cannot be improved without degrading at least one of the other objectives. Formulating this rule in mathematical terms would be: 1) a decision vector $x^* \in S$ is Pareto-optimal only when there is not another $x \in S$, that $(x) \leq (x^*)$ for all $i = 1, \ldots, k$; 2) $f_j(x) \leq f_j(x^*)$ for at least one index of $j$.

- Pareto-optimal decision vector is defined by $(S)$, and according to this, the objectives vector is defined by $(Z)$.

- There is an existing set of weakly Pareto-optimal solutions, where the set of Pareto-optimal solutions is a subset of. A decision vector $x^* \in S$ is considered as a weakly Pareto-optimal if there is not another $x \in S$, that $(x) \leq (x^*)$ for all $i = 1, \ldots, k$. The weakly Pareto-optimal decision vector is defined by $(S)$, and according to this, the objectives vector is defined by $(Z)$.

- The upper and lower bound are defining the feasible range of Pareto-optimal solutions. The lower bounds of an optimal set are defined by the ideal objective vector $z^* \in R^k$, where its values are obtained by minimizing individually all of the objective functions. The upper bounds are usually hard to be obtained.

- The set of feasible solutions can be defined as $C = \{y = R^n: y(f), x \in S\}$, where the curve AB is pareto frontier of all non dominated solution (Figure 6)

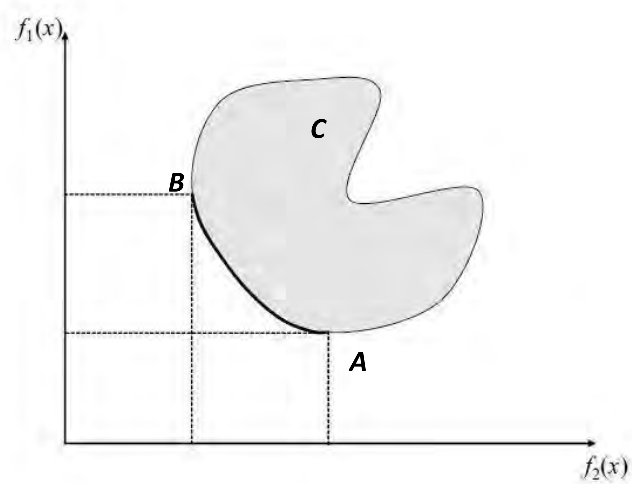



Figure 7: Pareto Frontier

Having the set of Pareto-optimal solutions does not mean that the optimal solution has been picked up. At this point, there is the need of the decision maker that should give priorities to one over another solution, since there are more than one objectives that should be taken into considerations. In order to arrive to this point, various methods are aiming at finding the set of Pareto-optimal solutions.

Obtaining the set of optimal solutions however is not a straightforward process, and is more complex than the standard single-objective optimization, since there are conflicting objective functions, with dependent variables. Therefore, many methods in the past have been invented for solving this kind of problems, which can be generally divided in two classes: Traditional or Basic Methods, and Evolutionary Algorithms. In order to design this research in a proper way and secure a good procedure for the problem solving, both of the topics are explained. In specific, three of the most diffused traditional methods are explained for the first topic, while for the second one an insight of Genetic Algorithms is explained, where two of the most sophisticated algorithms are presented in details. This should give an overview of the possible solving techniques, and give an idea of which method is better over another.

### 3.1.3 Traditional Methods

#### 3.1.3.1 Weighting Method

The weighting method, known also as a "scalarization" method is the most basic one for multi-objective problems. It is actually an approach that is combining several objective functions into a single one. It can

be mathematically formulated as:

$$minimize \sum_{i=1}^{k} w_i f_i(x) \tag{19}$$

$$Subject\ to: x \in S, \tag{20}$$

Where $w_i \geq 0$ for all $i = 1, \dots, k$, and the sum of all the weights should be $\sum_{i=1}^{k} w_i = 1$. This approach is converting a multi-objective problem into a single objective function by assigning weights for the importance of different objectives $(x)$. This is a method that needs an experienced person who knows the problem or a decision maker , which requires a certain performance level from an optimization model, to set the weights for the objectives. However, by only one setting of the weights, only one optimal solution can be obtained. This method can be easily transformed into an iterative one, by giving different weights to the objectives, aiming at a higher set of optimal solutions and obtaining the Pareto frontier.

Although the approach with various weights can derive the Pareto-optimal set, for non-convex problems there is the possibility of not finding any feasible solutions for any variety of weights Figure 11. Nevertheless, for relatively simpler convex problems, the setting of the weights can be a tricky task, since by changing the weights even for small instances, solutions can jump and leave big gaps in between. The dependence between the weights and the outcome of the solution sometimes can be hardly understood, making it even more difficult when the objectives are dependent on each other. All of these issues can mislead the decision maker to wrong directions, even though receiving solutions that may seem reasonable.

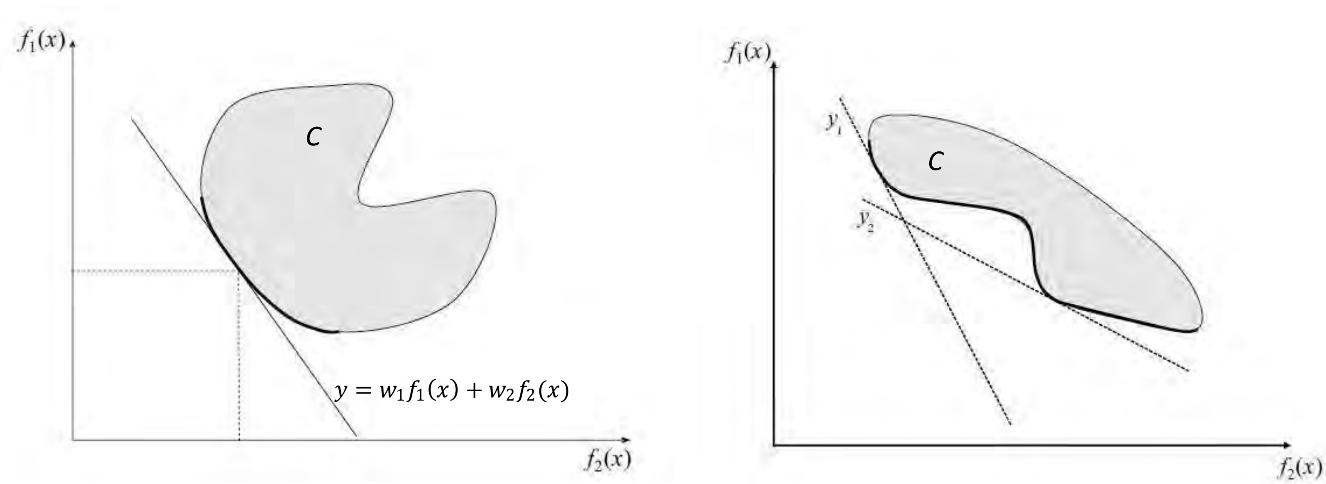



Figure 8: Pareto curves for Convex and Non-convex functions

Another drawback that is present in this method is related to producing unique solutions, which is really important for the decision-making process. There is a possibility that for a small change in the weights, same solutions to be obtained. There is a need of dramatically changing the weights, which can also lead towards big gaps between solutions or going out from the feasible region. Hence, this is a very costly procedure in terms of time, and nevertheless requires a lot of experience from the decision maker and the analyst that is doing the optimization, since every problem have different settings, and every model behaves in a different way.

#### 3.1.3.2 ε - Constraint method

This method is another approach that is transforming a multi-objective optimization problem, but in a different way. The method includes a prioritization of one objective function, which is set as

the function to be minimized, while the rest of the objective functions are transformed in constraints. The

mathematical formulation can be defined as:

$$Minimize\ f_l(x) \tag{21}$$

$$Subject\ to: f_l(x) \leq {}_j \qquad \forall j = 1, \ldots, k,\ j \neq l \tag{22}$$

$$x \in S \tag{23}$$

Where $l \in \{1, \ldots, k\}$, and ${}_j$ are the upper boundaries that have to be set for the objective functions transformed as constraints. This method, just as the weighted method, requires different settings for every objective function in order to search for the optimal set of solutions. Otherwise, solving it just once, it can be obtained only one solution that can be hardly considered as optimal. However, this method can be used both for convex and non-convex problems, which is overpassing the drawback of the weighted one.

The role of the decision-maker in this approach is also significant, since it is his decision which function is going to be set as an objective one, and his experience is also important for the definition of the upper bounds. There is however, a big risk of having a really good solution close to the upper bound, but on the other, infeasible side of the feasible region (Figure 28). This is significant drawback of this method, which cannot assess whether a good solution is present in this region or not. Another drawback are the settings of the problem, which have to be done in an iterative way, with more than one combination of objective functions and constraints, which is becoming even more complex when the numbers of objective functions is increasing. The importance of the objective functions and the various combinations of setting them as constraints are increasing the complexity of the iterations, as well as in the afterwards processes of solutions analysis.

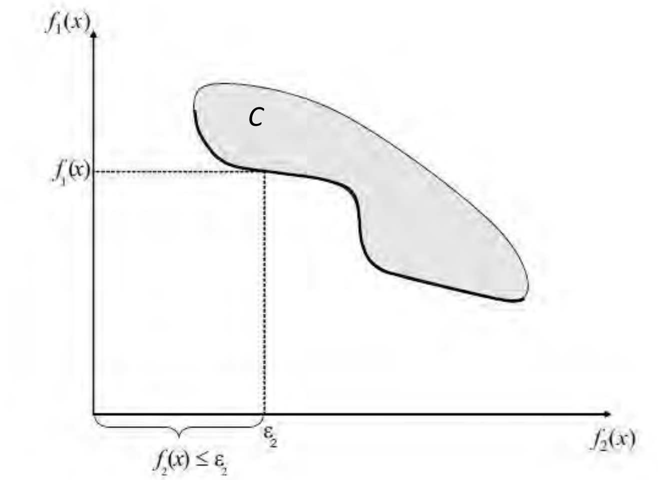



Figure 9: Obtaining a Pareto Frontier with the ε-constraint Method

**3.1.3.3 Goal Programming**

This is an approach that is widely used, and one of the most popular methods in general, for solving multi-objective problems. The reason behind its diffusion lays in its intuitive formulation and procedure of obtaining solutions. In the previous approaches an objective function was minimized, while in the goal programming the deviations from the target values of every objective are minimized. Thus, goal setting by the decision maker is a more intuitive approach than the previous ones, since it correlates to the business behavior of the problem itself.

A goal in this approach is the bundle of an objective function with its target level. In order to minimize the deviation from the target level, the goals are taking the form of $f_i \leq \overline{z_i}$ and the target levels $\overline{z_i}$ should be chosen in a way that does not allow to be achieved simultaneously for two or more objective functions. After setting the goals, it can be proceeded towards minimizing the deviations, which can be formulated as $\delta_i = \max\,[0, -\overline{z_i}]$. For all the objective functions $f_i$ the deviation $\delta_i$ can be formulated at the maximum value out of 0 and the difference from the target level. In order to find optimal solutions, this approach is using the target levels to form a feasible point, where a solution is considered as feasible if the deviations from that reference point is minimal. However, this is not necessarily a part of the Pareto optimal solution. Therefore, the goal programming is giving good results only when the target levels are pessimistic and restricting the area of optimal solutions.

Anyway, even though this approach does not include the actual objective functions in the minimization problem, it still needs a “scalarization” procedure for setting up multi-objective formulations. There are several variants, out of which the Weighted Goal Programming and Lexographic Goal Programming are the most diffused ones. The first approach is based on the earlier explained method, and is minimizing the weighted sum of the deviations. It can be formulated in the following way:

$$minimize \sum_{i=1}^{k} w_i \delta_i(x) \tag{24}$$

$$Subject\ to: f_i - \delta_i \leq \bar{z_i} \qquad \forall i = 1, \ldots, k \tag{25}$$

$$\delta_i \geq 0 \qquad \forall i = 1, \ldots, k \tag{26}$$

$$x \in S \tag{27}$$

In this modification of the goal programming, the decision maker besides the target levels, it should define also the weights, which increases the complexity of the solving procedure. The issues of assigning weights is already discussed in the section dedicated to the Weighting Method.

Another approach that is widely used for prioritization of the objectives is the Lexographic method, where the decision maker makes an order of objective functions to be minimized. After the first one is optimized, it should be preserved its value in the following objective function minimization, by setting up constraints. However, in the Lexographic Goal Programming, the objective functions are still substituted by the deviations and the constraints from (25) - (27) are used.

Even though the goal programming method is suitable for bigger problems, with more objective functions and more variables, the drawbacks embedded from the scalarization and weighting method are still existing. Finding the optimal set of solutions can be still a tricky task, since the deviations from the target levels can mislead the decision-maker, namely because of the conflicting functions and dependence between variables.

### 3.1.4 Evolutionary Algorithms

As discussed previously, the traditional methods have many drawbacks that are embedded in their solving approaches, where they fail in finding a set of optimal solutions, or they even fail at finding the global Pareto-optimal. Therefore, for optimizing multi-objective problems, new types of algorithms recently have been more and more diffused. The main advantage of these new methods are that they simultaneously with a set of possible solutions. By confronting the objective functions and analyzing at the same time various trade-offs, solutions of the overall set of Pareto-optimal are generated every single run of the algorithm. This was not a case in the traditional methods, where every new run one solution out of the Pareto-optimal set is generated. The dependency on the weights and parameters is avoided here as well by the generation of populations and setting up operators that are improving the solutions, without the need of the previous procedures. Thus, the solutions here are not sensitive on the weights and constraints definition, as well as the iteration's settings.

Another strong reason for using Evolutionary Algorithms in MOO is that complex problems, with numerous objective functions, variables and constrains can be implemented and solved without problems. Furthermore, the dependency on the decision maker from the traditional methods is no longer existing here, in the priory stages of the optimization, since the setting and population of the model is done by the algorithm itself. Like this, a more robust approach is conducted, where the continuity of the Pareto frontier is not having the issues of the gaps and jumps between solutions, from the traditional methods.

Nevertheless, it can be concluded that searching for a global optimum solution as in the traditional methods is not efficient. The decision-making process has the need of faster ways for generating bigger sets of Pareto-optimal solutions, that will not be focused on a specific decision, but will give a comprehensive picture of the optimization of the overall problem. This has the origins in designing of new products, were the variety of solutions and the conflicting trade-offs between objectives are emphasized strongly. Thus, having a variety of close-enough (to the optimal) solutions are favored in these algorithms in front of the obtaining process for just one global optimal solution.

Evolutionary Algorithms, especially the Multi-objective Evolutionary Algorithms (MOEA) are aiming at minimizing the distance between the solutions generated and the Pareto-optimal set, while maximizing the diversity in creating unique solutions. The approach that is followed lays down in the human genetics, where the mutation of the genes, and the reproduction processes are taken as a guideline for developing these algorithms. In fact, the most representative group of EAs are the Genetic Algorithms, which are fostering the idea of using an initial population and by combination and mutation of the genes of the solutions, iteratively to arrive towards a Pareto-optimal set of solutions. Genetic algorithms, searching from a population of points, seem particularly suited to multi-objective optimization. Their ability to find global optima while being able to cope with discontinuous and noisy functions has motivated an increasing number of applications in engineering and related fields. The GAs are created by John Holland in the middle '70s and have a variety of implementation fields, classified mainly in engineering, industrial and scientific. Some of the areas where are mostly applied are: electrical engineering, hydraulics, aeronautics, robotics, controlling, telecommunications, design and manufacturing, management, scheduling, supply chain design, as well as sciences like physics, medicine and computer science.

### 3.1.4.1 Genetic Algorithms

Genetic Algorithms are structured in a certain way, which enables from a set of random or predetermined population, in numerous generations to be obtained satisfactory non-dominated Pareto-optimal solutions. The algorithm is permitting a combination of parts from various solutions in order to be constructed better and more resistant ones. In particular, on Figure 29 is shown the workflow chart of the general principle of working, which includes initial population operations and several operators for performing specific tasks in order to enable better generations of quality solutions.

### 1. Initial Population

If there is an existence of knowledge on the problem or past optimization data, the initial population can be conducted by those. Otherwise, the GA begins the process with a random population.

### 2. Representation of Population

The solution procedure uses binary string, thus the solution is a string code of fixed length. In order to use real data, there is a necessity of transforming it into fixed-length binary strings, for enabling the computers to process the solutions.

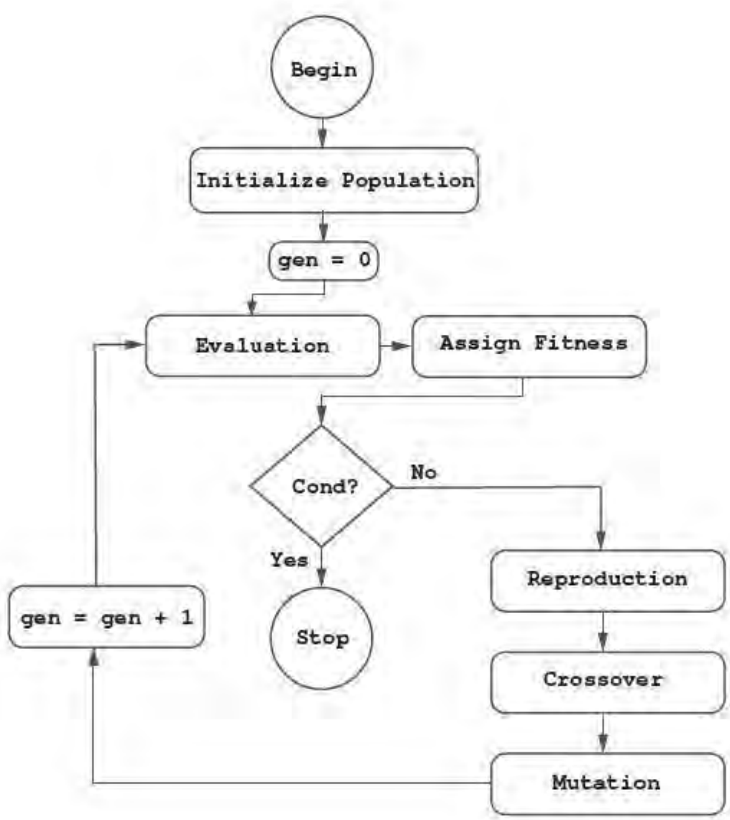



Figure 10: Working Principle of a Genetic Algorithm

$$\underbrace{1001011}_{X_1}\quad \underbrace{11001}_{X_2}\quad \underbrace{101011}_{X_3}\ \dots\ \underbrace{1101100}_{X_k}$$

### 3. Fitness Assignment

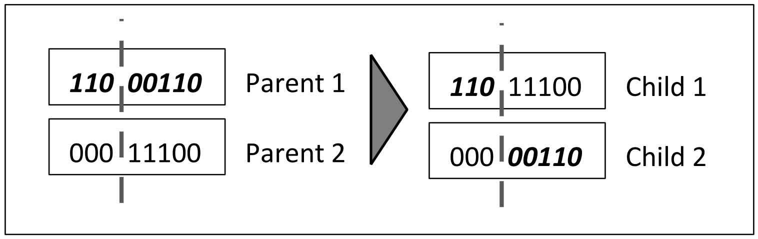
Based on the objective function relation, every string created, has to be assigned a fitness value. This is valid for both the initial populations, as well the generations following out of the iterations of the algorithm. Based on whether is minimization or maximization objective function, different fitness are assigned to the strings. For a minimization problem, the string gets the reciprocal value of the objective function, while for maximization ones the string is equal to the objective function value. Like this, solutions related to a lower function are being assigned a larger fitness.

### 4. Reproduction

Starting with the reproduction, the operators' process initiates. This operator makes the selection of the good strings from every population and creates a mating pool. The idea is to have picked up the good strings with good genes, where a replication of the string is created and inserted in the mating pool. There are various reproduction operators, which are typical for various algorithms. Therefore, this issue is addressed in the following explanation of specific GAs.

### 5. Crossover

Once having the selected above average performing strings, the crossover operator can be applied. Basically this step is taking portions from different parent's strings and combining them in new strings, i.e. the children. The aim is good strings to be created by combining good genes, which will create more copies in the next generations. On the contrary, if a bad string is created by the crossover, it will not survive the next generation, since it would not be selected for the mating pool in the previous step. However, the purpose of the crossover is not just to combine the strings, but to store as well the information from the parents in order to enable constant creation of good solutions. Just like in the reproduction step, the crossover can be done in various ways, depending on the specific algorithm.




### 6. Mutation

The mutation operator is changing single element in a particular string in order to maintain or improve the diversity in the population. While the crossover aimed at searching and combining good genes, the mutation tends to enlarge the chances of a string to get closer to an optimum by changing a value from 0 to 1 or vice versa. This change is done by some probability, which varies from an algorithm to an algorithm, or from an optimization model to another.

The main goal of the working principle of a GA is clear, improving the initial population iteratively by applying operators who are combining the strings aiming at improving the solutions. The substrings created from the strong strings are to survive, and to contribute towards a better reproduction and crossover. However, this is the general structure of a GA, which has been modified so far by researchers, in order to improve the efficiency of the algorithms in general or for specific problems. One of the most important and diffused GAs, are the Multi-objective Genetic Algorithm (MOGA), and the Non-dominated Sorting Genetic Algorithm (NSGA). These are advanced algorithms, which evolved through time from the general structure of a GA. They are specifically dedicated to multi-objective optimization and based on Pareto ranking of the solutions. Therefore, the focus is set on these two approaches, where the characteristics are explored in details in order to evaluate the performance and choose the most suitable one as a solving method.

## 3.1.5 MOGA – Multi-objective Genetic Algorithm

MOGA is developed by (Fonseca and Fleming, 1993), and is an algorithm that has a specific procedure of ranking the individual strings by a special fitness function. The steps on Figure 31 are constructing the MOGA (Tan et al., 2005). The first step is ranking the individuals according to the Pareto scheme, where smallest fitness values are assigned for all the non-dominated strings, while the dominated are ranked according to the number of other strings in the population that are dominating them. If there is a string $x_i$ at a generation $t$ which is dominated by $p_i^{(t)}$, the ranking of the string is given by:

$rank(x_i, t) = 1 + p_i^{(t)}$ (M1).

Thus, all the non-dominated strings are given a ranking of 1, while the rest are given values according to the number of strings that are dominating them (Figure 30). After the rankings are calculated, the fitness should be assigned according the ranking of the strings, starting from $(x_i, t) = 1$ until $r(x_k,t) \leq K$ (Goldberg and Holland, 1988). The fitness can be calculated as an inverse rank, where $(x_i, t) = in(rank(x_i, t))$ (M2), which should satisfy the condition of $(rank(x_i, t) < rank(x_j, t)) \Leftrightarrow (fit(x_i, t) > fit(x_j, t))$. The goal is to average the fitness of individuals with the same rank, so that all of them will be sampled at the same rate. This should maintain a global population fitness constant.

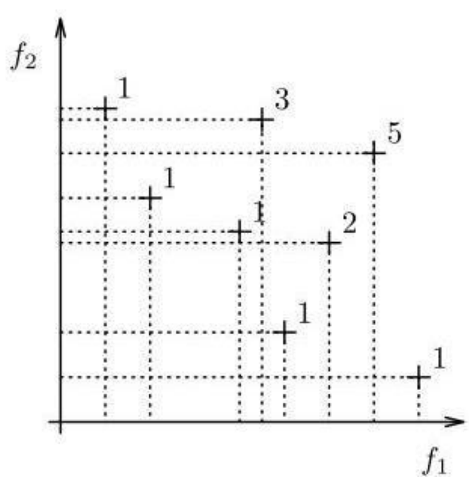



Figure 11: Multi-objective Ranking of Strings (Deb et al., 2002)

Another improvement that is implemented in the MOGA, is permitting a better uniform distribution of the population along the Pareto frontier. This is done by implementing fitness sharing in the objective value domain rather than the decision variable domain, and only between pairwise non-dominated individuals (Fonseca and Fleming, 1993). Therefore, it is introduced a new sharing parameter called $\sigma_{share}$ that is showing how far two strings should be from each other in order to decrease their fitness. The sharing of the fitness between the individuals is given by:

$fit'(x_i, t) = sharing(fit(x_i, t), S) = \frac{fit(x_i,t)}{\sum_{j=1}^{P} SF(i,j)}$(M3),

Where $S$ is the space, for which the sharing is performed and $P$ is the population of strings between whom the sharing of fitness is done. $SF$ is the amount of sharing contributed to each string, determined by the proximity of the strings, and the sharing distance. The formation method for distributing the population over the population region here is done for maintaining diversity of the objective function values.

Overall MOGA is an efficient algorithm, but fails at maintaining the diversity of the parameter set, which is important for the decision-making process. Another important drawback is not being able to find multiple solutions in problems where different Pareto-optimal points correspond to the same objective function value.

```
Initialize generation counter: n = 0.
Create a population, Pop.
Repeat while stopping criterion is not met.
        Evaluate Pop for all objective function values, F.
        Based on (M1), compute rank value rank(i) for each individual.
        Based on (M2), compute fitness value fit (i) for each individual.
        Based on (M3), compute shared fitness fit'(i) for each individual.
        Perform genetic selection on Pop based on the shared fitness.
        Perform genetic crossover and mutation on Pop with or without mating restriction.
        n=n+1.
End Repeat
Evaluate Pop for all objective function values, F.
Based on (M1), compute rank value rank(i) for each individual. Let rank = {rank(i): ∀i =
1,…, P}.
Based on (M2), compute fitness value fit (i) for each individual.
Based on (M3), compute shared fitness fit'(i) for each individual.
Return (Pop, F, rank,…).
```

Figure 12: Main Loop of MOGA (Deb et al., 2002)

### 3.1.6 (NSGA) - Non-dominated Sorting Genetic Algorithm (NSGA)

NSGA is an algorithm proposed by (Srinivas and Deb, 1994), where the idea of a non-dominated sorting of the populations is still present, but they try to resolve the drawbacks of the MOGA by presenting several layers of classifications of the individuals (Coello, 2001). It is proposed firstly the population to be ranked based on domination (same as MOGA), and furthermore all of the strings that are non-dominated to be set in the same group and assigned a large dummy fitness value. The same fitness value is given to all the individual strings in order to give equal opportunity for reproduction. Afterwards, the procedure of sharing (same as MOGA) is performed in order to maintain diversity in the population. Finally, before reproducing, another dummy fitness value is assigned to every string, but now with a smaller value than the previous values respectively. Like this, the strings with maximum fitness values are providing more copies in the population, and the algorithm permits faster convergence towards the non-dominated Pareto-optimal.

Even though the NSGA tries to address the problems of MOGA, and improve the non-dominant sorting, on the improvement of the diversity of solutions are emphasizing three major critics on these two approaches:

1. High computational complexity for the non-dominated sorting, which makes these algorithms expensive when large population sizes are implemented. The complexity of the procedure is because of the performing operations at every generation.

2. Lack of elitism, where the loss of good solutions is prevented by implementing this approach. Elitism permits the best strings of the population to move forward in the generations without being changed.

3. The sharing parameter needs to be specified. This parameter is core for enabling diversity in the population, and the performance of the algorithms is highly dependent on it. However, the procedure of specifying it is complex, not standardized and not efficient enough (Fonseca and Fleming, 1998).

In fact, in the same publication an improvement of these algorithms and in general of evolutionary algorithms is proposed, as a part of the second generation of GAs. The authors are developing a new ***Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II,*** based on the first version of NSGA.

The NSGA-II presents few improvements, which are based on the new fast and elitist sorting of the population, a new selection operator for creating a mating pool by combining strings from parents and children, and a new crowded-comparison approach for maintaining the diversity. Furthermore, it is proposed a simple approach for handling constraints for practical applications.

The new fast sorting follows several steps. First, the number of solutions $n_p$ that are dominating a solution $p$ is calculated, and second, the set of dominated solutions $S_p$ by solution $p$ are calculated. All of the non-dominated solutions that are part of the first optimal frontier are having domination counted as 0. All of the solutions that are dominated by a $n_p = 0$ from the set of $S_p$ are having a reduced domination by -1. Like this the second frontier is defined, where furthermore the rest of the solutions are set in a list $Q$ and the procedure continues until the last frontier is identified.

In order to solve the problems with the sharing factor, this algorithm proposes a new method called crowded-comparison approach, where the complexity is reduced and the dependence on the outside decision for the sharing factor is avoided. In order to be done this step, the density estimation should be performed. It defines the density of solutions surrounding a particular solution in a population, by calculating the average distance of two points on either side of the point along each of the objectives. Furthermore the crowding-distance computation requires sorting of the populations according to the objective function value. After having them sorted by objective function, they are assigned an infinite distance value for the solutions that are on the boundary, while for the rest of the intermediate ones a distance value equal to the absolute normalized difference in the function values of two adjacent solutions. These distances serve for the calculation of the overall crowding-distance value.

```
fast-non-dominated-sort(P)
for each p ∈ P
  S_p = ∅
  n_p = 0
  for each q ∈ P
    if (p ≺ q) then                 If p dominates q
      S_p = S_p ∪ {q}               Add q to the set of solutions dominated by p
    else if (q ≺ p) then
      n_p = n_p + 1                 Increment the domination counter of p
  if n_p = 0 then                   p belongs to the first front
    p_rank = 1
    F_1 = F_1 ∪ {p}
i = 1                               Initialize the front counter
while F_i ≠ ∅
  Q = ∅                             Used to store the members of the next front
  for each p ∈ F_i
    for each q ∈ S_p
      n_q = n_q − 1
      if n_q = 0 then               q belongs to the next front
        q_rank = i + 1
        Q = Q ∪ {q}
  i = i + 1
  F_i = Q
```

Figure 13: Fast Non-dominated Sorting in NSGA-II (Deb et al., 2002)

The algorithm forms a set of non-dominated solutions that are being part of the comparison of how crowded are the solutions. The solutions that are favored, are the ones that have lower rank (closer to the most optimal frontier), or when solutions from the same frontier are analyzed, the one that is less crowded is more valued. By combining the fast ranking and the new selection operator, this algorithm significantly increases the efficiency of the solutions' generation.

The third improvement that is presented in the algorithm is in its working principle, and how actually is performing the steps. First of all the population $R_t$ is combined out of the parents $P_t$ and the children $Q_t$. By including these two types of previous and current strings, the elitism is assured. Furthermore, the non-dominated fast sorting is performed, where a set of strings are rejected. Afterwards, by the new sorting operator, the variety of the solutions is maintained by assuring a certain distance between the solutions of the same frontier and between frontiers. At the end, the new population $P_{t+1}$ is created for the next generation.

As a final improvement of the NSGA-II the constraint-handling procedure is presented, which uses binary tournament selection, where a better solution out of two is chosen. The two solutions can be both feasible, one of them feasible, or both of them unfeasible, therefore the choosing of the solution is done by feasibility, and then between them, the one with smaller overall constraint violation is chosen to proceed. The presentation of the constraints-handling procedure re

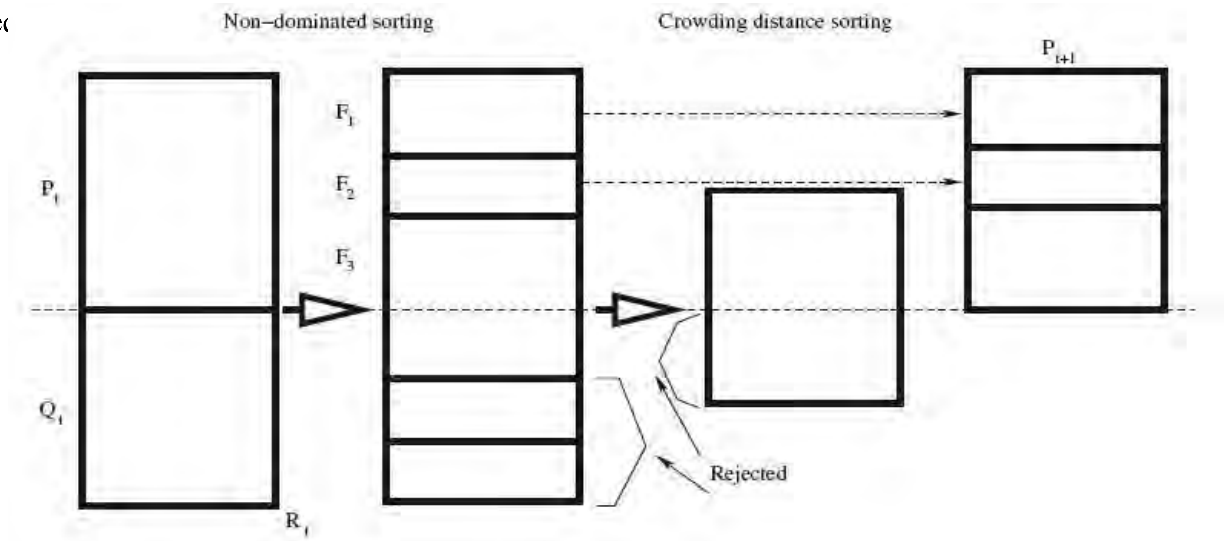



Figure 14: Fast Non-dominated Sorting in NSGA-II (Deb et al., 2002)

modification of the definition for the domination between two solutions. Therefore, a solution $i$ is constrained-dominant over solution $j$ if any of the following expressions are valid:

1. Solution $i$ is feasible, while $j$ is not.
2. Both of the solutions are infeasible, but $i$ has a smaller overall constraint violation.
3. Both of the solutions are feasible, and $i$ dominates $j$.

As an overall conclusion, it can be said that the NSGA-II is the best algorithm from the above presented. The main strengths of it, over the others, is the fast sorting of the population, which increases the efficiency, the elitist approach which permits good strings to proceed in the generations and contributes towards better solutions, as well as the better maintaining of the variety of solutions along the Pareto optimal frontier. Moreover, the simplification of the constraints handling is an additional feature, which permits an easy practical usage. Therefore, the NSGA-II is used as a solving algorithm for obtaining tradeoff Pareto-optimal solutions in the following chapters. However, it is considered as a feasible and satisfactory option, but not as the optimal one. The optimality and applicability of the algorithm are discussed after the analysis of the solutions, where a better picture of the performance is available.

# Chapter-4

# Model Formulation

## 4.1 Problem Identification

An important component in SCN design and analysis is the establishment of appropriate performance measures. A performance measure, or a set of performance measures, is used to determine efficiency and/or effectiveness of an existing system, to compare alternative systems, and to design proposed systems. These measures are categorized as qualitative and quantitative. Customer satisfaction, flexibility, and effective risk management belong to qualitative performance measures. Quantitative performance measures are also categorized by: (1) objectives that are based directly on cost or profit such as cost minimization, sales maximization, profit maximization, etc. and (2) objectives that are based on some measure of customer responsiveness such as fill rate maximization, customer response time minimization, lead time minimization, etc.

The network design problem is one of the most comprehensive strategic decision problems that need to be optimized for long-term efficient operation of whole supply chain. It determines the number, location, capacity and type of plants, warehouses, and distribution centers to be used. It also establishes distribution channels, and the amount of materials and items to consume, produce, and ship from suppliers to customers. SCN design problems cover wide range of formulations ranged from simple single product type to complex multi-product one, and from linear deterministic models to complex non-linear stochastic ones.

In recent years, the supply chain network (SCN) design problem has been gaining importance due to increasing competitiveness introduced by the market globalization. Firms are obliged to maintain high customer service levels while at the same time they are forced to reduce cost and maintain profit margins. Traditionally, marketing, distribution, planning, manufacturing, and purchasing organizations along the supply chain operated independently. These organizations have their own objectives and these are often conflicting. But, there is a need for a mechanism through which these different functions can be integrated together. Supply chain management (SCM) is a strategy through which such integration can be achieved.

## 4.2 Problem statement

The problem considered in this paper is an imaginary situation that can be applicable for any generic supply chain network consisting of suppliers, plants, distribution centers and customer zone. Therefore, in general it's a three echelon multi-product supply chain network in which an arbitrary company produces two set of products by using two raw materials and tries to achieve maximum customer service level (Demand Fill Rate) within minimum possible transportation time.

It has been considered that the company has two plants for converting the raw materials into finished products. In the first echelon raw materials are purchased from two suppliers depending on the minimum cost. In the second echelon two plants transport the finished products to two different distribution centers and finally in the third echelon the DCs transport the products to potential customer zones. Hence, the number and location of plants and customers, along with demands and capacities respectively, are known. The scenario based uncertainty has been incorporated in the model. A certain probability has been assigned for determining the likelihood of occurrence of that particular scenario. Under a certain scenario the customer demand, operating cost and capacity of different suppliers, plants and DCs are assumed uncertain. But, due to the use of scenario based uncertainty these parameters are used directly from the raw data and hence uncertainty is considered for occurring the scenario.

Another important point to be noted is that the effect of disruption has also been considered in model formulation. It has been assumed that whenever any disruption is occurred or emergency situation is arisen, a particular supplier becomes unavailable and the amount of raw materials those could have been purchased from that supplier need to be outsourced at a reasonably higher cost.

Obviously, a probability has been assigned for a particular supplier to represent the likelihood of becoming unavailable in disruptive or emergency situation.

The distribution centers and plants must be selected from a discrete set of potential locations with fixed opening costs and limited capacities. In the second and third echelon transportation channels consist of vehicles and routes are chosen by different selected plants and DCs based on the minimum vehicle and routing cost as well as minimum transportation time. The transportation of the product from one facility to the other in each echelon of the network is done selecting one of several alternatives available. Each transportation channel represents a type of service with associated cost and time parameters. These alternatives can be obtained from offers of different companies, the availability of different types of service for each company (e.g. express and regular), or the use of different modes of transportation (e.g. truck, rail, airplane, ship or inter-modal). It was assumed that a faster service is usually more expensive. The capacity of the transportation channel was assumed as unlimited, considering that any capacity can be contracted.

So, the trade-off between costs, transportation time and customer service level leads the author of this work to formulate a mixed integer tri-objective SCN optimization model. One criterion tries to minimize the fixed cost of selecting suppliers, plants and distribution centers and fixed transportation cost for different vehicles and routes as well as variable cost of transporting one unit of raw materials from suppliers to plants and one unit of finished products from plant to DCs and DCs to customer zones. The other two criteria covers the transportation time for different vehicles and routes and customer service level respectively.

## 4.3 Assumption of the study

Some assumptions have been considered while designing the multi-objective SCN optimization problem.

The main assumptions of the provided model are:

i. The structure of the supply chain is fixed
ii. The formulation is a single-period, multi-product model

iii. The operational costs, the customer demand, and the capacity of the facilities are stochastic parameters.

iv. Outsourcing costs are reasonably more expensive than the total average costs per unit product.

v. Scenario based uncertainty has been incorporated by using a known probability of occurrence of certain scenario

vi. The probability of becoming unavailable for particular supplier under emergency condition is known.

vii. Each plant has a limited capacity.

viii. All customers should be served.

The number of available vehicles for each type and the number of allowed routes for each DC are limited

**i.** There are several modes of transportation between two consecutive levels.

**ii.** Between two nodes on an echelon, only one type of vehicle is used.

**iii.** A faster transportation mode is the more expensive one

To determine all feasible routes, the following factors are taken into account:

**i.** Each customer should be visited by only one vehicle.

**ii.** Each route begins at a plant and ends at the same plant for second echelon and for third echelon it starts from a DC and ends at the same DC.

**iii.** Transportation cost for the first echelon will be covered by the supplier and hence selection of transportation channel for the first stage is beyond the capacity of the formulated model in this research.

**iv.** The sum of the demands of the customers served in each route must not exceed the capacity of the associated vehicle.

**v.** Each of the distribution center and the vehicle have various limited, and determined capacity

## 4.4 Mathematical Modelling

This research, for the first time proposed an integrated approach for designing a multi-objective three echelon supply chain network design model under scenario based uncertainty for the joint optimization of cost, transportation time and customer service level. The specific objectives of this model are mentioned below:

- **i.** Minimization of cost (Fixed cost, variable cost, fixed transportation cost and outsourcing cost) designated by $f_1$
- **ii.** Minimization of transportation time by selecting suitable vehicles and appropriate route from available alternatives designated by $f_2$
- **iii.** Maximization of customer service level (Demand fill rate) designated by $f_3$

Before proceeding to the mathematical model, some parameters and variables of the model are introduced in the following:

### 4.4.1 Sets and Indices

R = set of raw materials indexed by r

F = set of finished products indexed by f

S= set of suppliers indexed by s

K= set of plants indexed by k

J= set of distribution center indexed by j

I= set of customer zone indexed by i

N= set pf scenarios indexed by n

$V_{kj}$= set of all feasible routes between node k and j

$Z_{ji}$= set of all feasible routes between node j and i

$L_{kj}$= Set of vehicles connecting node k and j indexed by $l_1$

$L_{ji}$ = Set of vehicles connecting no0de j and I indexed by $l_2$

M= set of emergency situations indexed by m

### 4.4.2 Parameters

$E^{rf}$ = Amount of raw material r required in the production of one unit of product f

$b^{if}$ = Demand of customer i for product f in a particular scenario

$C_{sk}^{r}$= Fixed cost of providing raw material r to plant k by supplier s

$C_{kj}^{f}$= Fixed cost of providing finished product f to distribution center j by plant k

$C_{ji}^{f}$= fixed cost of providing finished product f to customer zone i by distribution center j

$B_{sk}^{rn}$= Unit cost of providing raw material r to plant k by supplier s

$B_{kj}^{fn}$= Unit cost providing finished product f to distribution center j by plant k

$B_{ji}^{fn}$= Unit cost of providing finished product f to customer zone i by distribution center j

$d_{sk}^{rnm}$= Out sourcing cost for one unit of raw Material r under emergency situation m when suppler s is blocked and plant k is involved

$C_{kjl1}$= Fixed transportation cost for transporting any product from plant k to distribution center j by vehicle $l_1$

$C_{kj}^{v}$= Fixed transportation cost for transporting any product from plant k to distribution center j by route v

$C_{jil2}$= Fixed transportation cost for transporting any product from distribution center j to plant k by vehicle $l_2$

$C_{ji}^{z}$= Fixed transportation cost of any product from plant k to distribution center j by route z

$TP_{kjl1}$ = Transportation time for shifting any product from plant k to Distribution center j by vehicle $l_1$

$TP_{kj}^{v}$= Transportation time for shifting any product from plant k to Distribution center j by route v

$TP_{jil2}$ = Transportation time for shifting any product from Distribution center j to customer zone i by vehicle $l_2$

$TP_{ji}^{z}$ = Transportation time for shifting any product Distribution center j to customer zone i by route z

$Q_{sk}^{r}$= Upper limit on the quantity of raw material r shipped from supplier s to plant k in a particular scenario.

$Q_{kj}^{f}$= Upper limit on the quantity of finished product f shipped from plant k to distribution center j in a particular scenario.

$Q_{ji}^{f}$= Upper limit on the quantity of finished product f shipped from Distribution center j to customer zone i in a particular scenario

$P^{n}$= Probability of occurring scenario n

$P^{m}$= Probability of occurring emergency situation m for which suppler s will be blocked

### 4.4.3 Continuous Variables

$x_{sk}^{r}$= Amount of raw material r shipped from suppler s to plant k in particular scenario

$x_{kj}^{f}$= Amount of Finished product f shipped from plant k to distribution center j in particular scenario

$x_{ji}^{f}$= Amount of Finished product f shipped distribution center j to customer zone i in particular scenario

### 4.4.4 Binary Variables

$Y_{sk}^{r}$= Decision to provide or not to provide raw material r to plant k by supplier s

$Y_{kj}^{f}$= Decision to provide or not to provide finished product f to distribution center j by plant k

$Y_{ji}^{f}$= Decision to provide or not to provide finished product f to customer i by distribution center j

$A_{kjl1}$= Decision binary variable equal to 1 if vehicle $l_1$ is used to transport finished product from plant k to distribution center j or 0 otherwise

$X_{kjv}$ = Decision binary variable equal to 1 if route v is used to transport finished product from plant k to distribution center j or 0 otherwise

$A_{jil2}$= Decision binary variable equal to 1 if vehicle $l_2$ is used to transport finished product from distribution center j to customer zone I or 0 otherwise

$X_{jiz}$= Decision binary variable equal to 1 if route v is used to transport finished product from distribution center j to customer zone i or 0 otherwise

### 4.4.5 Model formulation

Min $f_1$ = Fixed cost + Variable cost

$$=\sum_r \sum_s \sum_k C_{sk}^r Y_{sk}^r + \sum_f \sum_k \sum_j C_{kj}^f Y_{kj}^f + \sum_f \sum_j \sum_i C_{ji}^f Y_{ji}^f + P^n [\sum_r \sum_s \sum_k B_{sk}^{rn} x_{sk}^{rn} + \sum_f \sum_k \sum_j B_{kj}^{fn} x_{kj}^{fn} + \sum_f \sum_j \sum_i B_{ji}^{fn} x_{ji}^{fn}] + P^n P^m \sum_r \sum_s \sum_k d_{sk}^{rnm} x_{sk}^{rn} + \sum_k \sum_j \sum_{l1} C_{kjl1} A_{kjl1} + \sum_k \sum_j \sum_v C_{kj}^v X_v + \sum_j \sum_i \sum_{l2} C_{jil2} A_{jil2} + \sum_j \sum_i \sum_z C_{ji}^z X_z \quad (1)$$

$$\text{Min } f_2 = max_{(j)} (max_{k,l1} (TP_{kjl1}\, A_{kjl1}) + max_{k,j,v} (TP_{kj}^v X_{kjv}) + max_{j,I,l2} (TP_{jil2}\, A_{jil2}) + max_{j,I,z} (TP_{ji}^z X_{jiz})) \quad (2)$$

$$\text{Max } f_3 = (\sum_f \sum_j \sum_i x_{ji}^f) / \sum_{i,f} b_i^f \quad (3)$$

**Subject to,**

$\sum_s \boldsymbol{x_{sk}^{rn}} - \sum_f \sum_j E^{rf} \boldsymbol{x_{ji}^{fn}} = 0$ ∀ r and k *(4)*

$\sum_k \boldsymbol{x_{kj}^{fn}} - \sum_i \boldsymbol{x_{ji}^{fn}} = 0$ ∀ f and j *(5)*

$\sum_j \boldsymbol{x_{ji}^{fn}} \leq b^{if}$ ∀ f and i *(6)*

$\boldsymbol{x_{sk}^{rn}} - Q_{sk}^r Y_{sk}^r \leq 0$ ∀ r, s, k and n *(7)*

$x_{kj}^f - Q_{kj}^f Y_{kj}^f \leq 0$ ∀ f, k, j and n *(8)*

$x_{ji}^f - Q_{ji}^f Y_{ji}^f \leq 0$ ∀ f, j, i and n *(9)*

$\sum_k \sum_{l1} A_{kjl1} \leq \sum_k Y_{kj}^f$ ∀ j and f *(10)*

$\sum_j \sum_{l2} A_{kjl2} \leq \sum_j Y_{kj}^f$ ∀ i and f *(11)*

$\sum_{l1} A_{kjl1} \leq 1$ ∀ *k* and *j* *(12)*

$\sum_{l2} A_{jil2} \leq 1$ ∀ *j* and *i* (13)

$\sum_v X_{kjv} \leq 1$ ∀ k and j (14)

$\sum_z X_{jiz} \leq 1$ ∀ *j* and *i* *(15)*

$Y_{sk}^r = \begin{cases} 1 \\ 0 \end{cases}$ *(16)*

$$Y_{kj}^{f} = \begin{cases} 1 \\ 0 \end{cases} \quad (17)$$

$$Y_{ji}^{f} = \begin{cases} 1 \\ 0 \end{cases} \quad (18)$$

$$A_{kjl1} = \begin{cases} 1 \\ 0 \end{cases} \quad (19)$$

$$A_{jil2} = \begin{cases} 1 \\ 0 \end{cases} \quad (20)$$

$$X_{kjv} = \begin{cases} 1 \\ 0 \end{cases} \quad (21)$$

$$X_{jiz} = \begin{cases} 1 \\ 0 \end{cases} \quad (22)$$

$\boldsymbol{x_{sk}^{rn}}, x_{kj}^{f}, x_{ji}^{f} \geq 0$ (23)

The objective function $f_1$ minimizes the sum of total fixed cost and expected total variable cost. The fixed cost includes cost of selecting a particular supplier, plant and distribution center. Also, it includes fixed transportation cost for certain vehicles and route as well as variable cost of shifting one unit of raw material and finished product between facilities. Most importantly the seventh cost component in equation (1) or objective function $f_1$ represent the out-sourcing cost of procuring raw material when regular suppliers become unavailable for disruption or in emergency situation. The second objective function $f_2$ stands for the minimization of the total transportation time for shifting finished product from plants to customer zones through a particular distribution center. To, minimize the transportation time the selection of transportation channel in terms of choosing suitable vehicles and routes has been executed while running the optimization. Finally, the third objective function $f_3$ is used for the maximization of customer service level or demand fill rate which has been defined as the ratio of total amount of finished products delivered to a particular customer to the total amount of finished products demanded by that customer.

Equation (4) stands to ensure that total amount of raw material r shifted to plant k is equal to the total amount of all products made at this plant. Similarly, equation (5) ensures that all finished products that enter a DC also leave that DC. Equation (6) represents that total amount of finished products shifted to a customer is less than or equal to the total amount of products demanded by that customer. Equations (7), (8), (9) ensure that units of a commodity are provided from an origin to destination if and only if the mentioned origin is selected to provide the commodity to the mentioned destination. It has also been ensured that the capacity of different facilities are limited and amount of material transported from them does not exceed those capacity constraint. Equation (10), (11) confirms that if a facility (Plant and DC) is selected to provide product to a particular destination (DC or Customer Zone) only then a vehicle is used to transport product from that selected facility to particular destination.

Equation (12), (13), (14), (15) strand for the confirmation that if two facilities are related to each other, then one type of vehicle transport products between them through a certain route and obviously the vehicle and route will be chosen depending on the minimum cost and minimum transportation time. Equation (16 to 22) represent the binary nature of some variables already defined in variables section. And, finally equation 23 signifies the non-negative nature of three variables.

Therefore, in general the problem is defined as try-objective mixed integer program. As a solution procedure Non Dominated Sorting Based Genetic Algorithm (NSGA-II) was used to obtain the pareto optimal set since, NSGA-II is best suited to solve such kind of multi-objective optimization problem. The implementation of this solution procedure was done in MATLAB. Finally, the solution was compared for different scenario after making trade off among the solution obtained in the pareto font.

# Chapter-5

## Model Testing

The mathematical model presented in Chapter 4 has to be tested for two reasons, first for its functionality to be proven, and second the outcomes and trade-offs between the conflicting objectives to be analyzed. Therefore, a test problem has to be designed, for which the model is solved with a specific solving technique, and at the end results from the tests can be analyzed and presented in a suitable way. For that reason, this chapter is divided in three sections:

**1.** Design of a Use Case and Data Population

**2.** Solving Method Characteristics

**3.** Presentation of Solutions and Trade-off Analysis

First of all a use case example is constructed and populated with all the necessary data. The example has to be suitable for testing the problem, in order to have proper outcomes for assessing the model. Furthermore, the solving method characteristics and settings have to be determined, for having an efficient approach towards the solving process. At the end, the actual tests should be performed, and the solutions analyzed in a proper way for having quality conclusions. Since this is a multi-objective problem, the attention is set on the various trade-off analysis.

### 5.1 Design of a Use Case and Data Population

When a testing problem has to be designed, several aspects should be taken into considerations. It can begin from the availability of data, and the possibility of having real business examples. If real case data is not available, maybe the complexity of the problem is too high. It can also be that this kind of problems at a given moment are not addressed in businesses, which can be included in the research. Furthermore, the transformation of the data for populating the models can be sometimes a highly complex task. Having the reasons above, and the complexity of the problem and innovations that are embedded in the model, as well as the problems that the research faced with finding real business case on which the model can be tested, gave some directions. It is chosen an option for designing a test problem specifically suitable for this research, based on a hypothetical supply chain, where the data is conducted by reasonable assumptions.

In particular, it is chosen a three level supply chain compiled out of two suppliers, two plants for converting raw materials to final product, two distribution centers (DC) and two customer zones to be served. The supply chain problem is assuming production of a two products, where two potential plants can be chosen for its production. The reason for these simplifications is partially explained above, but it lays in the complexity of the mathematical model. Since it is an NP-hard linear problem, leads towards the fact the solving this kind of problems can be a highly delicate procedure, where not just using evolutionary algorithms should be a standard way, but even developing new ones, or customizing the existing ones. This is considered as not efficient and reasonable to be done within a frame of this thesis research. However, the testing case can be upgraded in the future, where a more complex supply chain problem will be addressed. For this reason, there must be existing real data, and a specific action dedicated for designing

## 5.2 Model Data Population

In order to enable the solving of the model to generate concrete results, it has to be populated with data. For that reason a collection of data was performed, where data was picked from various sources, some reasonable assumptions were taken, and all the necessary calculations were done. For having a fully functional use case, the data was collected for several elements, mainly focused on the costs, transportation time, customer demand and capacities of the different facilities of the supply chain. Bellow, all the data is presented on the basis of the basis of the assumptions (hypothetical data).

**Table 1: Fixed cost (Money Units) of selecting supplier s, plant k & DC j for transporting material r, finished product f to plant k, DC j and Customer zones i (Where s=2; k=2; f=2)**

| $C_{sk}^{r}$ | | | $C_{kj}^{f}$ | | | $C_{ji}^{f}$ | | |
|---|---|---|---|---|---|---|---|---|
| **Notation** | **Scenario 1** | **Scenario 2** | **Notation** | **Scenario 1** | **Scenario 2** | **Notation** | **Scenario 1** | **Scenario 2** |
| C1 | 10000 | 20000 | C9 | 20000 | 40000 | C17 | 5000 | 10000 |
| C2 | 8500 | 17000 | C10 | 16000 | 32000 | C18 | 5500 | 11000 |
| C3 | 12000 | 24000 | C11 | 12000 | 24000 | C19 | 3500 | 7000 |
| C4 | 6500 | 13000 | C12 | 14500 | 29000 | C20 | 3000 | 6000 |
| C5 | 5000 | 10000 | C13 | 18000 | 36000 | C21 | 6000 | 12000 |
| C6 | 7500 | 15000 | C14 | 19000 | 38000 | C22 | 4500 | 9000 |
| C7 | 9500 | 19000 | C15 | 20500 | 41000 | C23 | 6500 | 13000 |
| C8 | 10500 | 21000 | C16 | 15500 | 31000 | C24 | 5500 | 11000 |

**Table 2: Unit cost of sending Raw material r & finished products f from supplier s, plant k & DC j**

| $B_{sk}^{rn}$ | | | $B_{kj}^{fn}$ | | | $B_{ji}^{fn}$ | | |
|---|---|---|---|---|---|---|---|---|
| Notation | Scenario 1 | Scenario 2 | Notation | Scenario 1 | Scenario 2 | Notation | Scenario 1 | Scenario 2 |
| B1 | 58 | 29 | B9 | 44 | 22 | B17 | 22 | 11 |
| B2 | 62 | 31 | B10 | 64 | 32 | B18 | 32 | 16 |
| B3 | 76 | 38 | B11 | 73 | 37 | B19 | 42 | 21 |
| B4 | 55 | 28 | B12 | 51 | 26 | B20 | 28 | 28 |
| B5 | 36 | 18 | B13 | 37 | 19 | B21 | 41 | 19 |
| B6 | 48 | 24 | B14 | 26 | 13 | B22 | 53 | 27 |
| B7 | 89 | 45 | B15 | 88 | 44 | B23 | 60 | 45 |
| B8 | 66 | 33 | B16 | 99 | 50 | B24 | 67 | 50 |

**Table 3: Upper limit on the quantity of raw material r and finished product f shipped from supplier s, plant k and DC j in a particular scenario.**

| $Q^r_{sk}$ | | | $Q^f_{kj}$ | | | $Q^f_{ji}$ | | |
|---|---|---|---|---|---|---|---|---|
| Notation | Scenario 1 | Scenario 2 | Notation | Scenario 1 | Scenario 2 | Notation | Scenario 1 | Scenario 2 |
| Q1 | 470 | 940 | Q9 | 115 | 230 | Q17 | 300 | 600 |
| Q2 | 600 | 1200 | Q10 | 250 | 500 | Q18 | 450 | 900 |
| Q3 | 250 | 500 | Q11 | 315 | 630 | Q19 | 770 | 1540 |
| Q4 | 420 | 840 | Q12 | 480 | 960 | Q20 | 530 | 1060 |
| Q5 | 860 | 1720 | Q13 | 660 | 1320 | Q21 | 940 | 1880 |
| Q6 | 610 | 1220 | Q14 | 530 | 1060 | Q22 | 680 | 1360 |
| Q7 | 970 | 1940 | Q15 | 910 | 1820 | Q23 | 850 | 1700 |
| Q8 | 1050 | 2100 | Q16 | 715 | 1430 | Q24 | 1000 | 2000 |

**Table 4: Demand of customer i for product f in a particular scenario, $b^{if}$**

| Notation | Scenario 1 | Scenario 2 |
|---|---|---|
| b1 | 10000 | 20000 |
| b2 | 20000 | 40000 |
| b3 | 7000 | 14000 |
| b4 | 25000 | 50000 |

**Table 5: Amount of raw material r required in the production of one unit of product f, $E^{rf}$**

| Notation | Scenario 1 |
|---|---|
| E1 | 2.5 |
| E2 | 1.5 |
| E3 | 1 |
| E4 | 1.5 |

**Table 6: Fixed transportation cost for transporting any product from plant k to DC j and from DC j to customer zone i for different vehicles**

| plant k to DC j $C_{jil2}$ | | DC j to Customer i | |
|---|---|---|---|
| Notation | Cost (m.u) | Notation | Cost (m.u) |
| C25 | 7000 | C33 | 2200 |
| C26 | 6300 | C34 | 1900 |
| C27 | 3200 | C35 | 1700 |
| C28 | 3600 | C36 | 2100 |
| C29 | 4700 | C37 | 3000 |
| C30 | 3900 | C38 | 2100 |
| C31 | 6200 | C39 | 150 |
| C32 | 6800 | C40 | 1800 |

**Table 7: Fixed transportation cost for transporting any product from plant k to distribution center j and from distribution center j to customer zone i for different route**

| plant k to DC j $C_{kj}^{v}$ | | DC j to Customer i $C_{ji}^{z}$ | |
|---|---|---|---|
| Notation | Cost (m.u) | Notation | Cost (m.u) |
| C41 | 3000 | C49 | 1000 |
| C42 | 2800 | C50 | 2000 |
| C43 | 4500 | C51 | 1500 |
| C44 | 3800 | C52 | 3000 |
| C45 | 7000 | C53 | 4000 |
| C46 | 8000 | C54 | 2500 |
| C47 | 6800 | C55 | 5000 |
| C48 | 7500 | C56 | 4000 |

**Table 8: Transportation time for shifting any product from plant k to Distribution center j by different vehicle and different route**

| Notation | Time (Time unit, hr) | Notation | Time (Time unit, hr) |
|---|---|---|---|
| T1 | 18 | T17 | 3 |
| T2 | 12 | T18 | 6 |
| T3 | 23 | T19 | 8 |
| T4 | 28 | T20 | 5 |

| | | | |
|---|---|---|---|
| T5 | 8 | T21 | 10 |
| T6 | 14 | T22 | 14 |
| T7 | 6 | T23 | 7 |
| T8 | 9 | T24 | 12 |
| T9 | 16 | T25 | 4 |
| T10 | 9 | T26 | 7 |
| T11 | 23 | T27 | 9 |
| T12 | 17 | T28 | 5 |
| T13 | 11 | T29 | 6 |
| T14 | 18 | T30 | 10 |
| T15 | 9 | T31 | 12 |
| T16 | 15 | T32 | 8 |

**Table 9: Probability values for different scenario**

| Scenarios | Occurrence probability of Scenario | Probability of being unavailable for supplier in emergency situation |
|---|---|---|
| Scenario 1 | 0.8 | 0.5 |
| Scenario 2 | 0.2 | 0.7 |

## 5.3 Solving Method Characteristics

For the solving process, as mentioned before in the Research Design, a fast and elitist Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used. For that reason a NSGA-II program in Matlab is used. This program is combining 16 Matlab scripts and 1 Graphic User Interphase (GUI) script that is plotting the results from the generations run. The complete code is presented in Appendix, while here the procedure of implementing it is presented.

In order to use the code, there are necessary adjustment that should be done. These adjustments are not in the scripts themselves, but in the way of writing the functions in a Matlab language. It was necessary to transform the mathematical formulation of the model into a specific programming language. While the writing of the code in the traditional linear solvers is intuitive, in this case there was a need of transforming the formulation model completely in the programming language. Moreover, in order the behavior of the algorithm to be understood, and test the mathematical model in a coded version, several small problems were run in order to define the best settings. Afterwards, the following parameters were set:

- The initial population is defined by using uniform distributed random numbers between the lower and upper bounds. This is done, since there is no existing previous optimization data.
- Initial population size: 700
- Maximum number of generations: 200
- Number of objective functions: 3
- Number of variables: 56 integer (Binary) variables, and 24 continuous variables.
- Number of constraints: 60

The code is implemented in Matlab R2013b, on a hp envy laptop with an i7 processor. Even though the speed was not a problem in the testing of the code, the assessment of the algorithm is out of scope for this research. There are no intentions of performing tests on the particular efficiency of the algorithm and comparing it with other approaches. Rather than doing that, it is used as a novelty in the optimization of supply chain network designs with triple bottom line approach, where it is aimed for generation of sufficient quality Pareto-optimal solutions.

## 5.4 Results and Trade-off Analysis

The results and trade-off analysis are performed in several levels, where various tests with different settings are aiming at answering the research questions. Thus, an overall optimization run is performed for the whole model, afterwards a test for the analysis of the cost, transportation time and at the end an analysis of the customer service level for completing the triple bottom line assessment. On various levels, different types of analysis are conceived, as well as different conclusions provided as an outcome.

For the first overall level of analysis, big optimization cycle was run, with an initial population of 700 and 200 generations.

On the second level of analysis, the single ranges of the functions were identified. The ranges of the objectives are important, since the decision maker can seek for solutions that are optimizing at best one particular objective, and according to that can search for solutions that are complementary.

## 5.5 Cost Function

**Table 10: Range of the value of Cost function**

| Objective Function | Range | |
|---|---|---|
| | Minimum Value | Maximum Value |
| Cost Function, f1 | 135685 | 344475 |

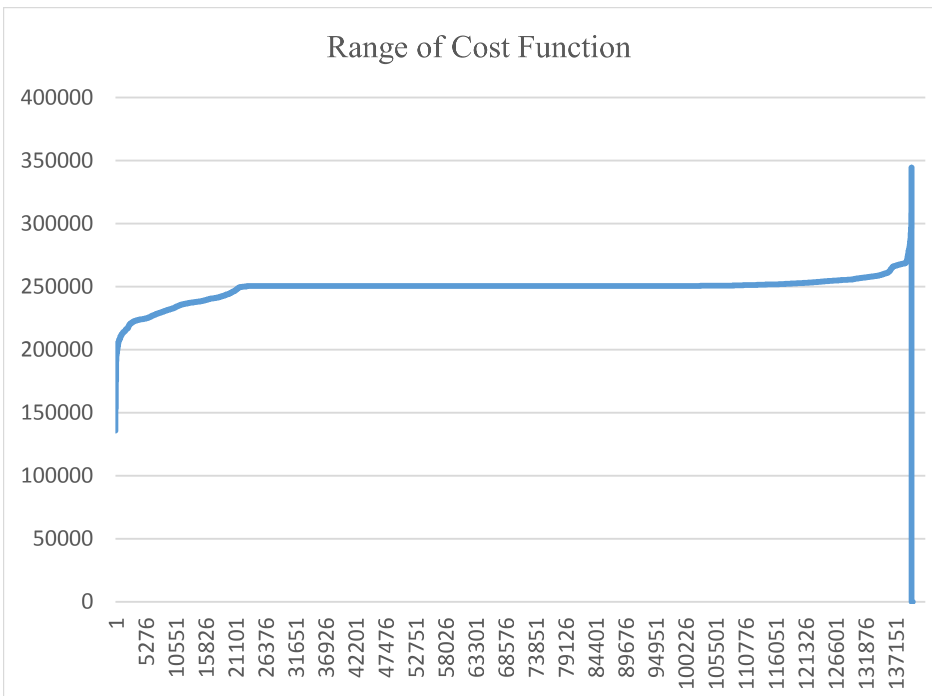



Figure 15: Range of Cost Function

The graph depicts that the minimum value of the cost function is 1,35,685 m.u, and the maximum value is 3,44,475 m.u. Within this band a lot of values exists with diversified values of decision variables. It should be noted from the figure () that for a appreciable number of solution of the pareto font the value of the cost function became stable at the value of approximately 2,50,000 m.u. The decision make can select any minimum value within this band for cost function and then corresponding value of transportation time and customer service level will have to selected if is interested to give priority to the cost function or in other words wants to set a supply chain network with minimum cost.

## 5.6 Transportation time Function

**Table 11: Range of the value of Transportation time function**

| Objective Function | Range | |
|---|---|---|
| | Minimum Value (hr) | Maximum Value (hr) |
| Transportation time Function, f2 | 29 | 118 |

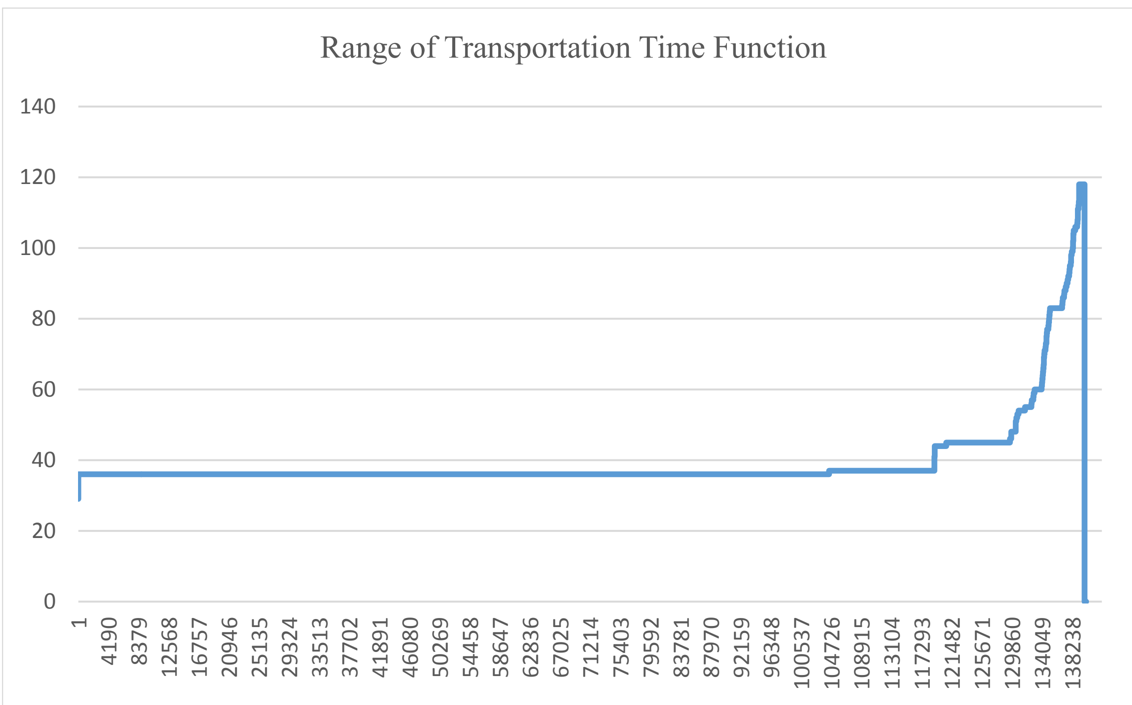



Figure 16: Range of transportation time Function

In case of transportation time function, with a view to determining the minimum value of this objective function, it should be observed in the figure that it is possible to transport any product from any plant to any customer zone through a particular distribution center within 29 hours, which is minimum. On the other hand, it can take maximum of 118 hours for the same transportation. In both of the case the minimum and maximum value obtainment depend on the selection of the shortest route and fastest vehicle and bice-versa. It is also clear from the graph that for a wide range of solution the value of the time function obtains stable figure of 36 hours. Again, there is the option to make trade off by selecting any value within this range and obviously to do that the decision make has to choose different value of other two functions respectively.

## 5.7 Customer Service Level

**Table 12: Range of the value of Service level function**

| Objective Function | Range | |
|---|---|---|
| | Minimum Value | Maximum Value |
| Customer Service Level Function, f3 | 0.0028235 | 0.0101824 |

**Table 13: Range of the value of Service level function for scenario 2**

| Objective Function | Range | |
|---|---|---|
| | Minimum Value | Maximum Value |
| Customer Service Level Function, f3 | 0.944655 | 1.000 |

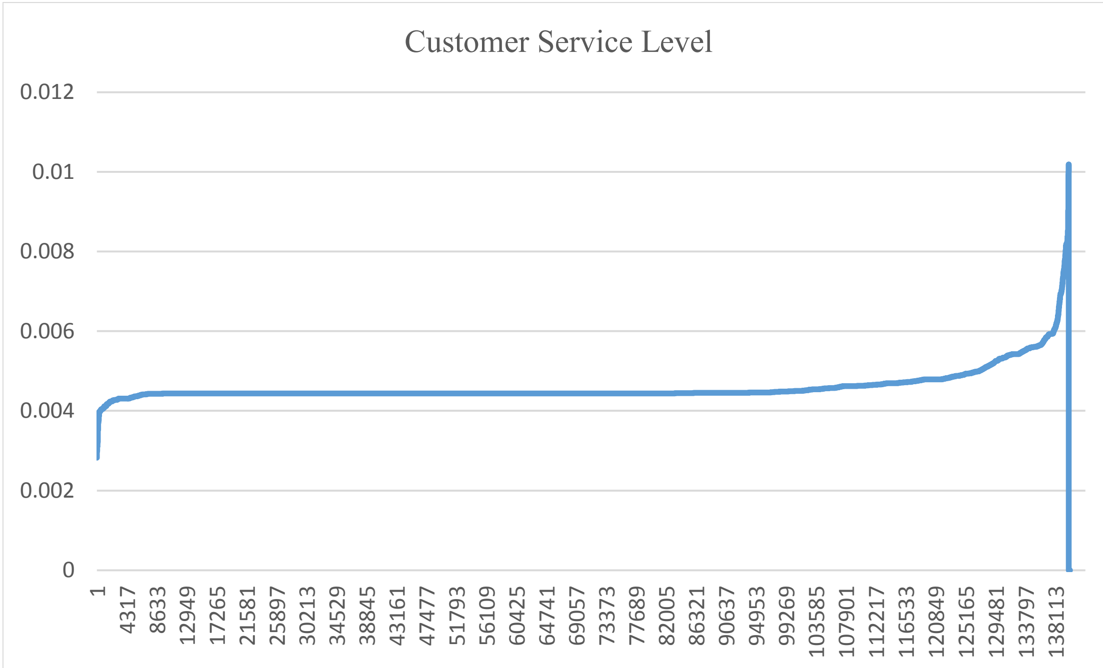



Figure 17: Range of service level Function

Unlike other two objective functions, the aim was to maximize the customer service level. Definitely, its conflicting nature influence the value of the other functions while choosing the maximum value of f3. The graph represents that the decision maker can select the supply chain network by ensuring the minimum cost and minimum transportation time but at the expense of minimum customer service level with a value of 0.0028235 and 0.944655 in scenario 1 and Scenario 2 respectively. On the contrary, the supply chain network can be responsive enough by ensuring the maximum service level of 0.0101824 for scenario 1 and 5.30167 for scenario 2 and to achieve this value there is no doubt that the value of the cost function will be increased. Like other two function there is a wide range within which the value of service level remain stable at the value of approximately 0.004 for scenario 1.

By presenting the characteristic of the objective functions individually, the process of analysis has a basis for continuing and analyzing the conflicted trade-offs between the objectives. Clearly, the aim of this model is to analyze the interaction between the objective functions, and to serve the decision-making process with data that will offer a variety of different solutions. Even though at this stage, the decision maker should step up with higher-level criteria for selecting solutions, the analysis is proceeding without it. For example, the decision maker can set the priorities of having the most cost effective supply chain by ensuring minimum transportation time, while the customer service level can have secondary importance. It can be even chosen the lowest cost solution for selecting cost effective supplier and for employing the low cost vehicle and without paying attention to the customer service level. However, in this case, for the research this kind of data is not necessary, in fact presenting the ability of the optimization has nothing to do with the higher-level criteria. Therefore, out of the non-dominated set of solution, for the analysis of the multi-objective optimization model, it is decided to pick up the solutions that are giving an equal importance to all three of the objectives.

In addition to the previous discussion, some graphs with the Pareto-Optimal solutions are presented. From **figures 21 - 26,** it can be seen how the solutions are initiating with a bigger population as highlighted by the figures attached below for lower generations, and afterwards are converging towards the most optimal line/surface. Just for clarification, the axis named "objective 3" has negative values due to the coding procedure for maximizing functions in Matlab, but nevertheless it should be evaluated as a positive number, which represents the customer service level.

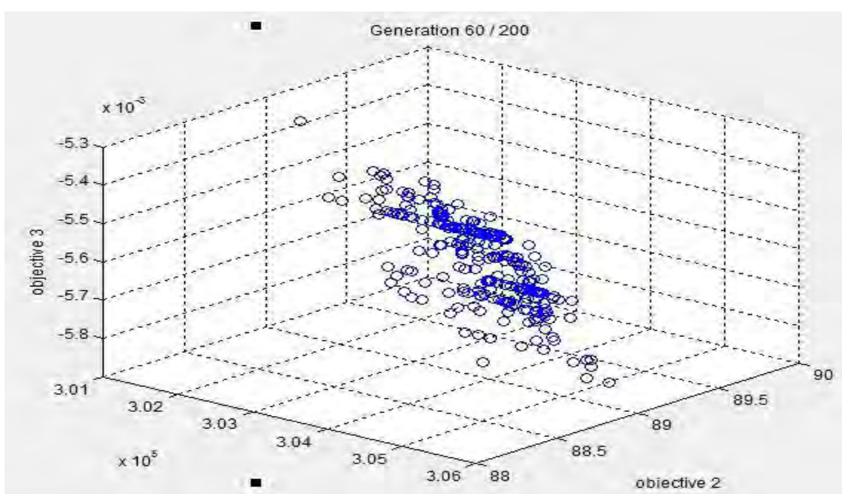



Figure 18: Pareto font of 52$^{nd}$ generation of 200

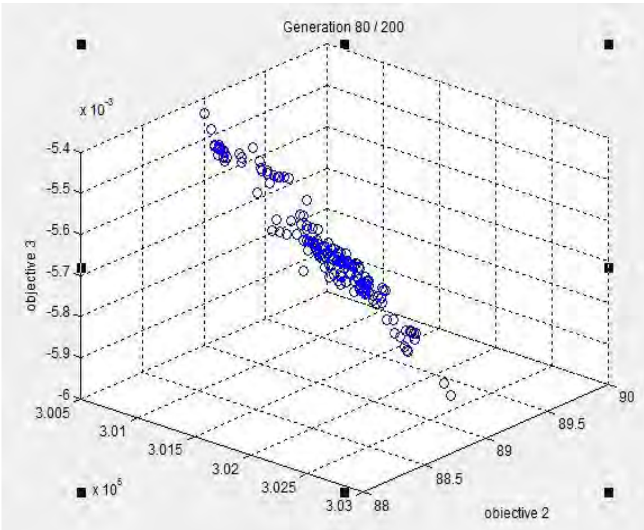



Figure 19: Pareto font of 80th generation

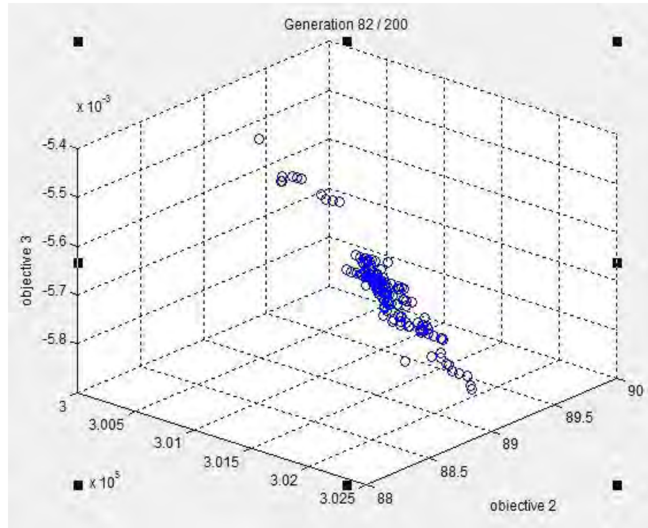



Figure 20: Pareto font of 82nd generation

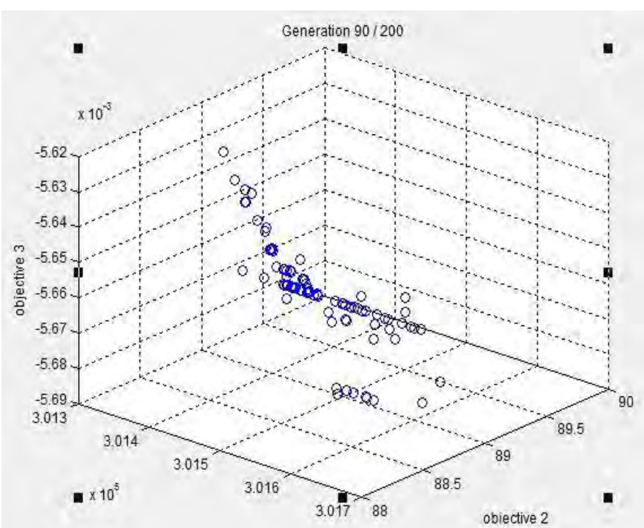



Figure 21: Pareto font of 90th generation

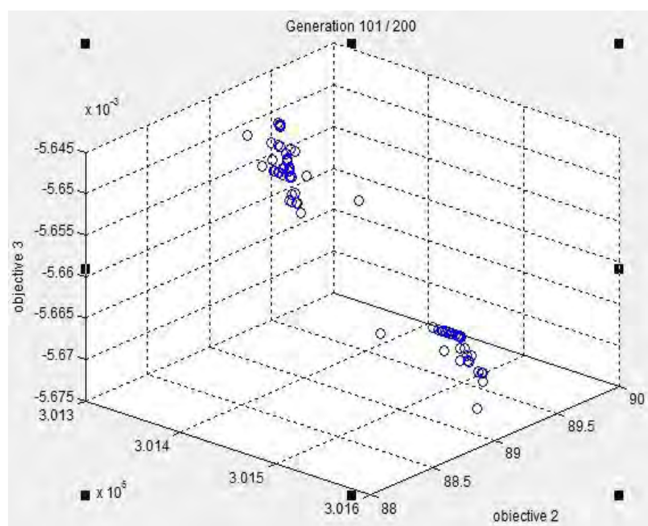



Figure 22: Pareto font of 101st generation

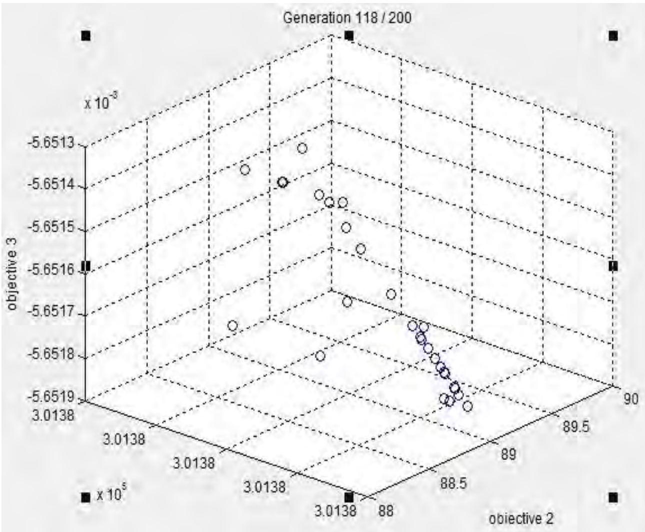



Figure 23: Pareto font of 118$^{th}$ generation

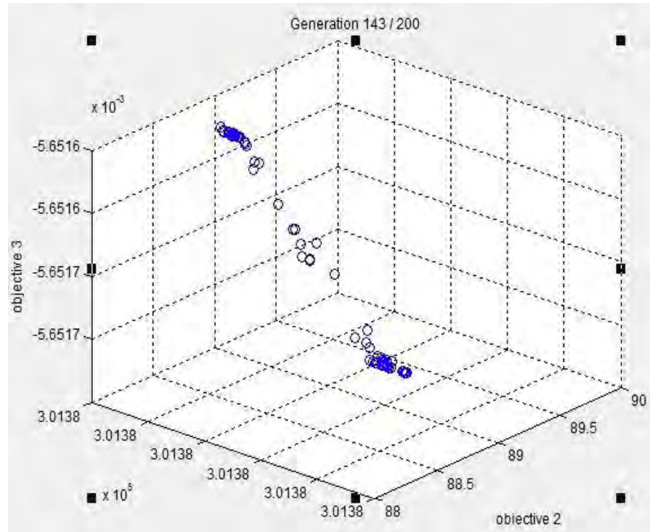



Figure 24: Pareto font of 143rd generation

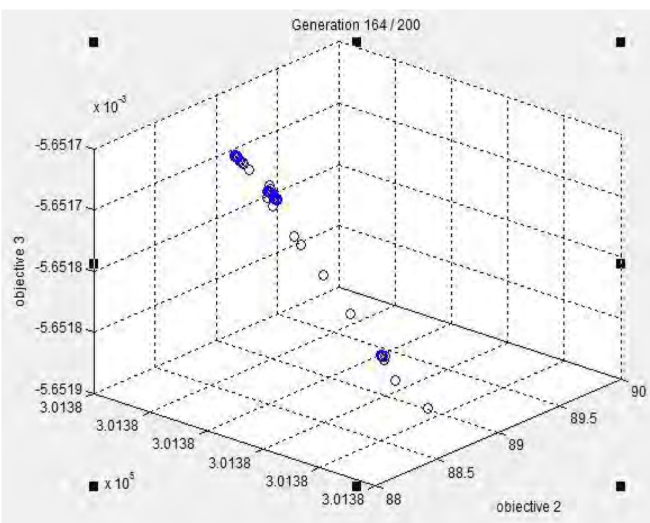



Figure 25: Pareto font of 154$^{th}$ generation

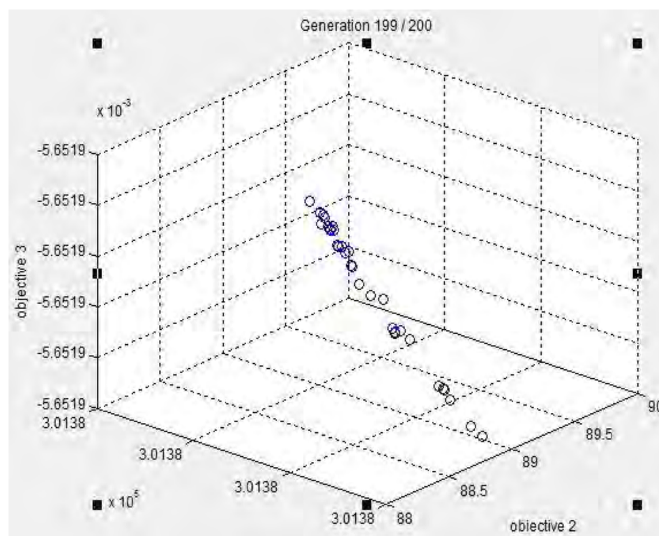



Figure 26: Pareto font of 199$^{th}$ generation

## 5.8 Analysis of decision variables for a set of solution

At this stage of analysis a set of solution has been elaborated with the values of three objective functions and associated values of 80 decision variables. This solution set has been taken from the pareto font generated for 70th generation.

**Table 14: Value of objective functions for a set of solution**

| Objective Function | Cost Function | Time Function | Service Level Function* 10000 |
|---|---|---|---|
| **Values** | 2,52,529 m.u | 36 Hours | 45.1904 |

**Table 15: Value of Decision variable for a set of solution**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **X1** | **X2** | **X3** | **X4** | **X5** | **X6** | **X7** | **X8** |
| 3.14561 | 0 | 1.45829 | 0 | 6.53194 | 0 | 1.12089 | 0 |
| **X9** | **X10** | **X11** | **X12** | **X13** | **X14** | **X15** | **X16** |
| 65.4535 | 75.3812 | 27.857 | 0 | 6.3662 | 16.0122 | 22.8801 | 67.2972 |
| **X17** | **X18** | **X19** | **X20** | **X21** | **X22** | **X23** | **X24** |
| 55.446 | 16.8982 | 33.2837 | 14.3735 | 92.5166 | 0 | 26.9021 | 40.76 |
| **X25** | **X26** | **X27** | **X28** | **X29** | **X30** | **X31** | **X32** |
| 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| **X33** | **X34** | **X35** | **X36** | **X37** | **X38** | **X39** | **X40** |
| 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| **X41** | **X42** | **X43** | **X44** | **X45** | **X46** | **X47** | **X48** |
| 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 |
| **X49** | **X50** | **X51** | **X52** | **X53** | **X54** | **X55** | **X56** |
| 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 |
| **X57** | **X58** | **X59** | **X60** | **X61** | **X62** | **X63** | **X64** |
| 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 |
| **X65** | **X66** | **X67** | **X68** | **X69** | **X70** | **X71** | **X72** |
| 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| **X73** | **X74** | **X75** | **X76** | **X77** | **X78** | **X79** | **X80** |
| 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 |

The value of the three objective functions are given in the table (14) and to obtain these values the decision variables are presented in the table (15) with their associated values. The variables denoted through X1 to X24 are designed in such a way that they should represent the real numbered values for amount of materials those are transported across the supply chain network. For the binary decision, variables X25 to X80 are used to select particular supplier, plant, DC, vehicle and route.

X25 to X32, X33 to X40 and X41 to X48 have been used as binary decision variables to select or not to select different suppliers, plants and DC to transport materials. X49 to X56 and X65 to X72 have been utilized as binary variables to represent whether to choose different vehicles and different routes from available alternatives for the second echelon of supply chain. Similar purpose have been served for the third echelon of designed supply chain network by the binary variables of X57 to X64 and X73 to X80.

X1 to X8 stand for the amount of raw materials shifted $(\boldsymbol{x_{sk}^r})$ to two plants from two suppliers for two types of raw materials. The value of X2=0 describes that no raw material of type 1 are transported from supplier 1 to plant 2. Similar, explanation can be given for X4, X6 and X8. This decision can also be strengthened by the corresponding zero values of binary variables X26, X28, X30 and X32 which gives the clarification that supplier 1 are not selected for transporting raw material of type 1 and 2 to plant 2. And it is also true for X30 and X32 in case of supplier 2, plant 2 and raw material type 1 and 2 respectively.

X9 to X16 $(\boldsymbol{x_{kj}^f})$ and X17 to X24 $(\boldsymbol{x_{ji}^f})$ stand for the amount of finished product shifted from plant to DC and DC to customer zones respectively. The value of X12 equal to zero i.e no finished product of type 2 are delivered to DC 2 by plant 1 and X22=0 describes that customer 2 does not receive any amount of finished product of type 1 from DC 2. Again, these two phenomena are clear from the zero values of two binary variables of X36 and X42 which clarified that plant 1 and DC 2 are not selected for finished product of type 2.

Variables X49 to X56 and X65 to X72 have been used as binary $(\boldsymbol{A_{kjl1}},\ \boldsymbol{X_{kjv}})$ to select or not to select the different vehicles and different routes respectively in the second echelon of the designed supply chain. X50=1 and X66=1 shows that vehicle 2 and route 2 have been used to transport material from plant 1 to DC 1. Similarly, X52=1 and X67=1 describes that vehicle 2 and route 1 have been chosen to transport material from plant 1 to DC 2. The zero value of some of the above mentioned variables indicates that corresponding vehicle and route are not selected in the second echelon.

Finally, decision variables X57 to X64 and X73 to X80 ($\boldsymbol{A_{jil2}}$, $\boldsymbol{X_{jiz}}$) have been used as binary for selecting transportation channel comprised of vehicles and routes in the third echelon. X57=1 and X74=1 clarifies that vehicle 1 and route 2 have been selected to shift product to customer zone 1 from DC 1. It can also be explained in the same manner for X60=1 and X75=1 i.e vehicle 2 and route 1 have been selected for the transportation of product from DC 1 to Customer zone 2.

At the end of analysis of the result of optimization, three set of solution of reasonable interval have been picked up for the sake of better realization of the trade-off among three objective function value presented in the table (16)

**Table 16: Comparison of the three solutions**

| **Objective function** | **Cost Function** | **Time function** | **Service Level Function*10000** |
|---|---|---|---|
| **Solution 1** | 1,35,685 m.u | 76 hr | 67 |
| **Solution 2** | 1,57.421 m.u | 56 hr | 50 |
| **Solution 3** | 3,23,111 m.u | 102 hr | 80 |

For solution 1 the value of the cost function is 1,35,685 m.u which is the minimum value of this objective function. At this level of cost of network, the minimum transportation time can be as minimum as 76 hrs and customer service level can be as maximum as 0.0067. The decision maker can choose this set of solution if he or she is interested to give priority to the cost function. Now, solution 2 highlights that the transportation time can be minimized to 56 hrs from 76 hrs as it was in the solution 1, but not without sacrificing other two objective function values, since it is clear for the **table 15** that the value of the cost function increase from 1,35,685 m.u to 1,57,421 m.u and service level reduced to 50 from 67. In the third solution this is evident that the value of the service level function increased to 80 which is very close to the maximum value of service level for this network. But, to achieve this value reasonably higher cost (3,23,111 m.u) is needed and for that the transportation time is also increased to 102 hrs. The reason behind this may be the higher value of the amount of material transported to DC from plant and to customer zones from DCs contributing to the higher value of total transportation cost of the network.

# Chapter-6

# Conclusion and Recommendations

## 6.1 Conclusion

In this thesis, a new model for multi-objective optimization of supply chain network (SCND) design is presented which has the goal of fulfilling and grasping some new research opportunities in the field of supply chain optimization. In this research, after identifying the research gaps in the field of supply chain network optimization, the objectives for the research design were formed. In particular, the model proposed is formulated as a MILP multi-objective optimization model, which addresses the triple bottom line approach. It is formulated out of three objective functions focused on minimizing the costs and transportation time, as well as maximizing the customer service level under scenario based uncertainty. The aim of the model is to optimize the design of supply chains network under uncertainty, by selecting the cost effective suppliers, plants and distribution centers (DCs). Moreover, the thesis also aimed to select the most effective transportation channels for the second and third echelon of designed supply chain network in terms of choosing suitable vehicle and routes from available alternatives. The model is applied to a hypothetical case example, designed for the purpose of this research, for proving its functionality and furthermore analyzing the outcomes from the optimization. During the thesis a lot of time have been spent to explore new advanced solving methodologies, which will contribute towards the generation of a better set of Pareto-optimal solutions. For that reason an analysis of two evolutionary genetic algorithms is performed MOGA and NSGA, where it is found out that both of them have certain drawbacks. In particular, they are having week sorting procedures and are failing in maintaining the variety of the solutions along the Pareto frontier. Therefore, a new second generation NSGA-II method is proposed, which is fast sorting and elitist algorithm, which is more efficient in sorting the population and guarantees better dispersion of solutions along the frontier.

Applying the algorithm is successful, where satisfactory results are obtained. With these, it has opened a new research opportunity for the optimization of sustainable supply chain designs.

Finally, even though this new model has some limitations, the applications of it can be found in the area of supply chain management and in designing the optimized supply chain network. Besides being a model dedicated to strategic supply chain designs, with certain modifications it can be used for optimizing or restructuring existing supply chains. It is supposed to be an engineering and management tool, rather than being a scientific one. Therefore, global corporations with robust supply chains, who are tending to implement effectiveness, efficiency and responsiveness in supply chain network can definitely benefit from this research.

## 6.2 Limitations and Future Recommendations

However, the model has some limits that should be taken into considerations for its future development. First, it is a single-period problem, where no in-between-stages inventory is taken into considerations. Second, it is a model that deals with scenario based uncertainty and does not include stochastic behaviors of the data. Including the stocasticity or uncertain behavior of future scenarios along with the stochastic nature of the data in such models should be taken into considerations, since nowadays with the global movement, future is hardly predictable. The issues of having a multi-period model and its stochastic behavior should be addressed simultaneously, since both of them should emphasize the dynamicity of the future model. Moreover, while considering the multi-period dynamic model under stochastic behavior of the data, inventory level and inventory holding cost can be incorporated with the application of stochastic programming to increase the robustness of the designed model.

In addition, even though there are not the main focus of such models, the excess demand production and service level penalties can be considered as a future upgrade. By including the aspect of the service quality and customer expectations the model can embed another important perspective, now more tactical one, which for sure will affect the current trade-offs.

Regarding the limits of the research, they are mainly located in the testing and analysis of solutions part. First of all, the usage of hypothetical data case is an important limit, since it does not completely replicate a real case situation. It is simplified, where only a single product case is tested, and the supply chain structure can be seen as a relatively small. This research is limited by the complexity of the model and finding a proper data in the period of the development. Therefore, the most suitable option was to design a specific dedicate case example. However, for the initial testing of the new model presented it is satisfactory and the test results are enabling quality analysis.

The other issue on the research limitation is related to the data analysis from the generations. During the research is felt the need of advanced techniques for big data analysis, which was not fulfilled. Every generation from the genetic algorithm is giving a big amount of data for every variable, objective function and constraints violation, which should be taken into considerations. Due to the complexity of data analysis, the optimization war run for only one scenario even though the data were available for the second scenario. Interested researchers can use those data and run the optimization for the second scenario and analysis the result of optimization for getting better insight of the model and to make necessary improvement as well. Thus, this research was limited in the efficient analysis of the data, where the conduction of conclusions was really time costly and certainly not error-proof.

All of the above issues mentioned on the limitations of the model and research can be considered as future possible improvement areas. However, from a modeling point of view, transforming the scenario based uncertainty model into a complete stochastic one can be one of the priorities in the first step. Furthermore, applying the model and testing it with real case data is an important phase that should confirm once again the findings and search for new potential ones. As a last step, studying in-depth genetic algorithms and developing a specific one for solving this kind of problems should be an important challenge. Along with this, new tools and methods for analyzing big data from GA's solutions generations should be developed. These future improvements are significant step forward in the multi-objective optimization for supply chains network optimization, which will certainly improve the models and will aim at identifying new trade-offs from the triple bottom line approach.

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# Appendix-1

## Matlab Code

```
% All praises are for Almighty Allah, who has made me able
function [y, cons] = echo_multiobjective(x, varExtra)
    % Code for the first objective function starts from here
    % Declare 64 values of c
    c = [10000 8500 12000 6500 5000 7500 9500 10500 20000 16000 12000 14500 18000 19000
20500 15500 5000 5500 3500 3000 6000 4500 6500 5500 7000 6300 3200 3600 4700 3900 6200
6800 2200 1900 1700 2100 3000 2100 1500 1800 3000 2800 4500 3800 7000 8000 6800 7500
1000 2000 1500 3000 4000 2500 5000 4000];
    s1=0; s2=0; s3=0;
    p = 25;
    a = 1;
   %constant c from 1 to 8 and variable x from 25 to 32
    for i=1:2
        for j = 1:2
            for k = 1:2
                s1 = s1 + c(a)*x(p);
                p = p+1; %p = 9 last value
                a = a+1;
            end
        end
    end

    % constant c from 9 to 16 and variable x from 33 to 40
    for i=1:2
        for j = 1:2
            for k = 1:2
                s2 = s2 + c(a)*x(p);
```

```
        p = p+1;
        a = a+1;
      end
   end
end
%constant c from 17 to 24 and variable x from 41 to 48%
for i=1:2
   for j = 1:2
      for k = 1:2
        s3 = s3 + c(a)*x(p);
        p = p+1;
        a = a+1;
      end
   end
end
% Declare 24 values of b %
b = [58 62 76 55 36 48 89 66 44 64 73 51 37 26 88 99 20 32 42 28 41 53 60 67];
s_4 = 0;
q = 1;

% constant b from 1 to 8 and variable x from 1 to 8%
for i=1:2
   for j = 1:2
      for k = 1:2
        s_4 = s_4 + b(q)*x(q); %a constant is to be multiplyed
        q = q+1;
      end
   end
end
constant1 = 0.8;
s4 = constant1*s_4;
```

```
s_5 = 0;
% constant b from 9 to 16 and variable x from 9 to 16
for i=1:2
    for j = 1:2
        for k = 1:2
            s_5 = s_5 + b(q)*x(q);
            q = q+1;
        end
    end
end
s5 = constant1*s_5;
s_6 = 0;
% constant b from 17 to 24 and variable x from 17 to 24%

for i=1:2
    for j = 1:2
        for k = 1:2
            s_6 = s_6 + b(q)*x(q);
            q = q+1;
        end
    end
end

s6 = constant1*s_6;
s_7 = 0;
r = 1;
% Declare 8 values of d %
d = [68 72 86 65 46 58 99 76];
% constant d from 1 to 8 and variable x from 1 to 8%
for i=1:2
    for j = 1:2
```

```
        for k = 1:2
            s_7 = s_7 + d(r)*x(r);
            r = r+1;
        end
    end
end
constant2 = 0.5;

s7 = constant2*constant1*s_7;
s8 = 0;
% constant c from 25 to 32 and variable x from 49 to 56%
for i=1:2
    for j = 1:2
        for k = 1:2
            s8 = s8 + c(a)*x(p); %a constant is to be multiplyed
            p = p+1;
            a = a+1;
        end
    end
end
t=1;
s9 = 0;
% constant c from 33 to 40 and variable x from 57 to 64%
for i=1:2
    for j = 1:2
        for k = 1:2
            s9 = s9 + c(a)*x(p);
            p = p+1;
            a = a+1;
        end
    end
```

```
  end
s10 = 0;
  % constant c from 41 to 48 and variable x from 65 to 72
  for i=1:2
     for j = 1:2
        for k = 1:2
           s10 = s10 + c(a)*x(p);
           p = p+1;
           a = a+1;
        end
     end
  end
  s11 = 0;
  % constant c from 49 to 56 and variable x from 73 to 80
  for i=1:2
     for j = 1:2
        for k = 1:2
           s11 = s11 + c(a)*x(p);
           p = p+1;
           a = a+1;
        end
     end
  end
  y(1) = s1+s2+s3+s4+s4+s5+s6+s7+s9+s10+s11;

  %End of first objective function code
```

Code for the Second objective function starts from here

```
% Declare 16 values of both TP1 and TP2 %
TP1 = [18 12 23 28 8 14 6 9 16 9 23 17 11 18 9 15];
TP2 = [3 6 8 5 10 14 7 12 4 7 9 5 6 10 12 8];
```

```
    W1 = max([T(1)*x(49) T(2)*x(50) T(5)*x(53) T(6)*x(54)])+ max ([T(3)*x(65) T(4)*x(66)
T(7)*x(69), T(8)*x(70)])+ max([T(9)*x(57) T(10)*x(58)])+ max([T(13)*x(59) T(14)*x(60)])+
max([T(11)*x(73) T(12)*x(74)])+ max([T(15)*x(75) T(16)*x(76)]);

    W2 = max([T(17)*x(51) T(18)*x(52) T(21)*x(55) T(22)*x(56)])+ max([T(19)*x(67)
T(20)*x(68) T(23)*x(71) T(24)*x(72)]) +max([T(25)*x(61) T(26)*x(62)])+ max([T(29)*x(63)
T(30)*x(64)])+ max([T(27)*x(77) T(28)*x(78)])+ max([T(31)*x(79) T(32)*x(80)]);
    y(2) = max([W1 W2]);
% End of second objective function code
% Code for the Third objective function starts from here

 % Declare 4 values of b1 constant %
    b1 = [10000 20000 7000 25000];
    s12 = 0;
    g = 17;
    %summation of variable x %
    for i = 1:2
        for j = 1:2
            for k = 1:2
            s12 = s12 + x(g);
            g = g + 1;
            end
        end
    end

    h = 1;
    s13 = 0;
    %summation of constant b1
    for i = 1:2
        for j = 1:2
            s13 = s13 + b1(h);
```

```
        h = h+1;
      end
    end
    y(3) = -1*(s12/s13);
%End of third objective function code

 inequalitiesViolation = [];
    equalitiesViolation = [];
    if(~isempty(varExtra.A))
            numberOfInequalities = length(varExtra.A(:,1));
            inequalitiesViolation = zeros(1,numberOfInequalities);
            for i=1:numberOfInequalities
                a = varExtra.A(i,:);
                b = varExtra.b(i);
                c = a * transpose(x) - b;
                if(c>0)
                    inequalitiesViolation(i) = c;
                end
            end
    end
    if(~isempty(varExtra.Aeq))
            numberOfEqualities = length(varExtra.Aeq(:,1));
            equalitiesViolation = zeros(1,numberOfEqualities);
            for i=1:numberOfEqualities
                a = varExtra.Aeq(i,:);
                b = varExtra.beq(i);
                c = a * transpose(x) - b;
                equalitiesViolation(i) = abs(c);
            end
    end
cons = [inequalitiesViolation, equalitiesViolation]
```

## Matlab Code for NSGA-II

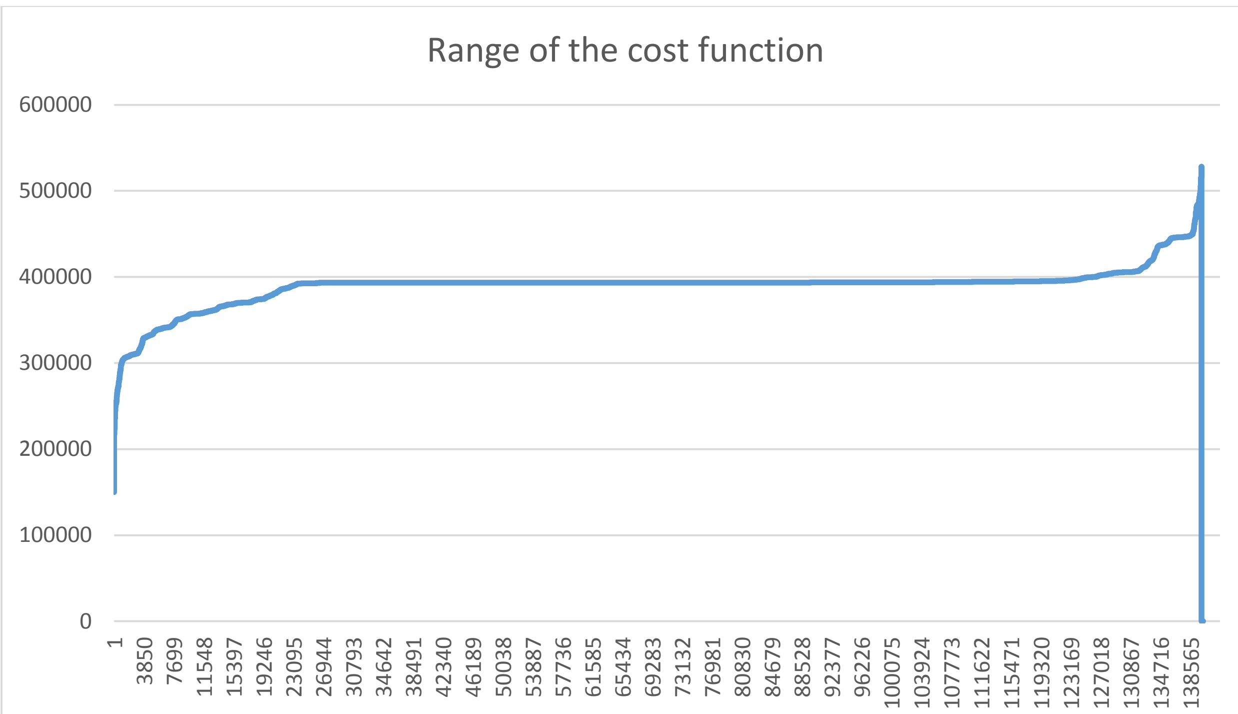
```
load('echo_multiobjective_data.mat');

% create default options structure
options = nsgaopt();
% population size
options.popsize = 700;
% max generation
options.maxGen  = 200;
% number of objectives
options.numObj = 3;
% number of design variables
options.numVar = 80;
%type of variable: integer=2 real=1
options.vartype = [ones(1,24),ones(1,56)+1];
% number of constraints
options.numCons = 60;
% lower bound of x
options.lb = LB ;
% upper bound of x
options.ub = UB;
% objective function handle
options.objfun = @echo_multiobjective;

% interval between two calls of "plotnsga".
options.plotInterval = 1;

%Pass the extra parameter for linear inequality.
extraParam = makeLinearInequality(options.numVar,options.numCons);

extraParam.A = A;
extraParam.b = b;
extraParam.Aeq = Aeq;
extraParam.beq = beq;

% begin the optimization!
result = nsga2(options,extraParam)
```

# Appendix-2

## Result of optimization of Scenario 2

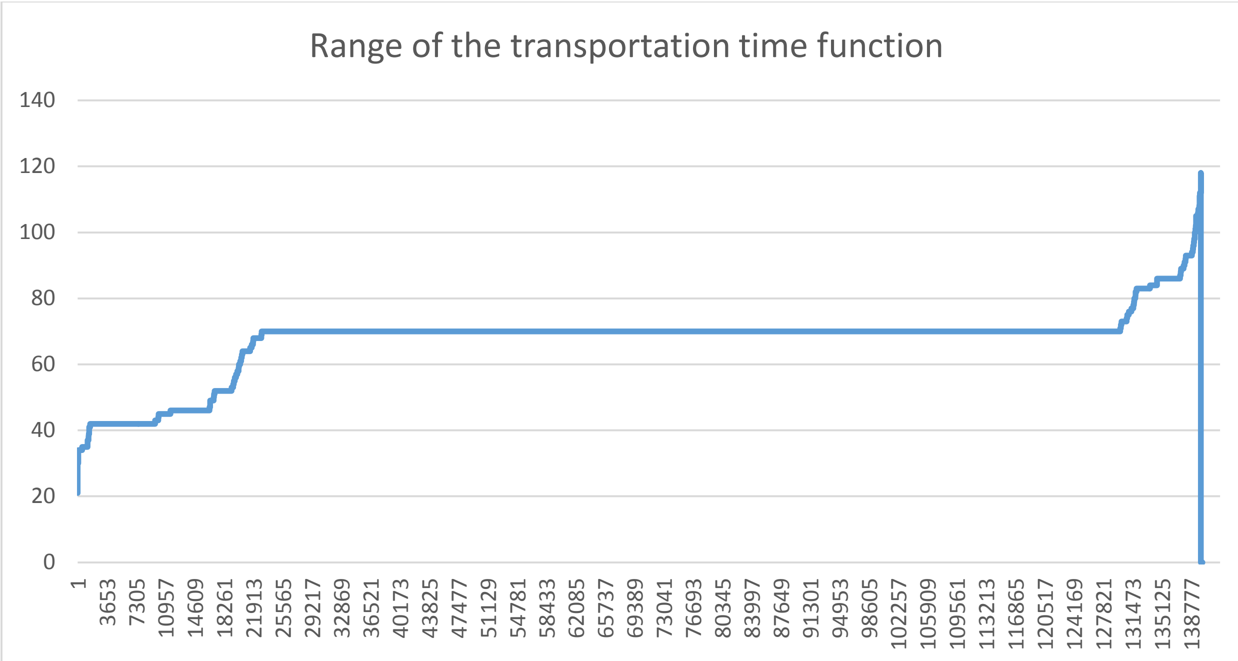
### Range of the value of Cost function

| Objective Function | Range | |
|---|---|---|
| | Minimum Value | Maximum Value |
| Cost Function, f1 | 1,50,219 m.u | 5,27,996 m.u |



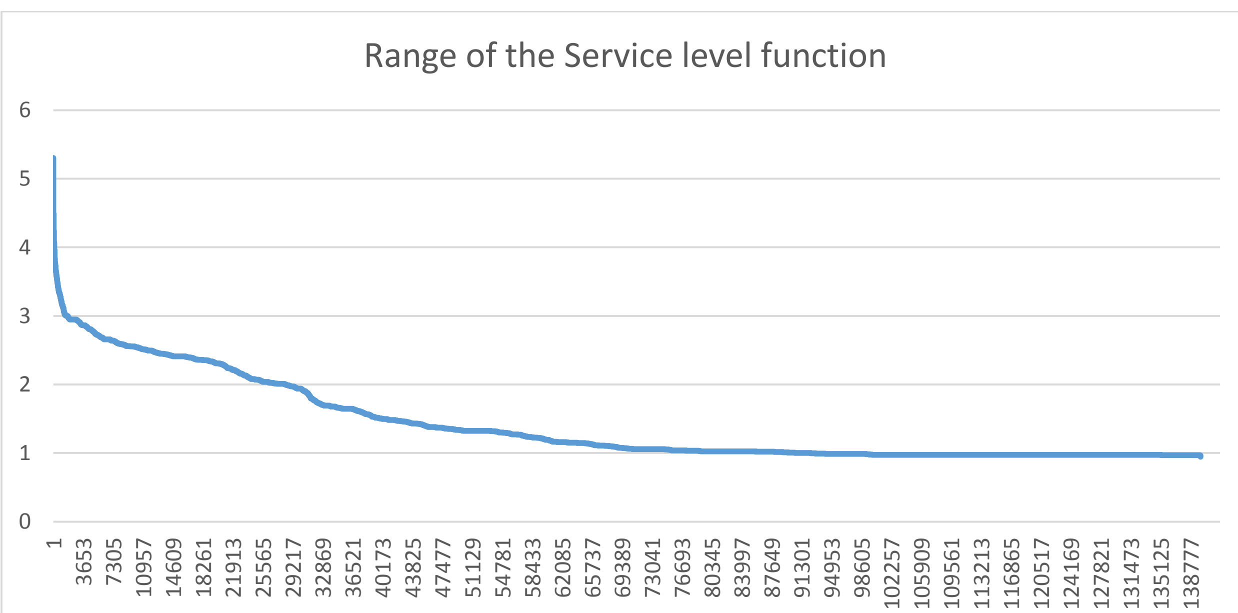

### Range of the value of Transportation time function

| Objective Function | Range | |
|---|---|---|
| | Minimum Value (hr) | Maximum Value (hr) |
| Transportation time Function, f2 | 21 | 118 |

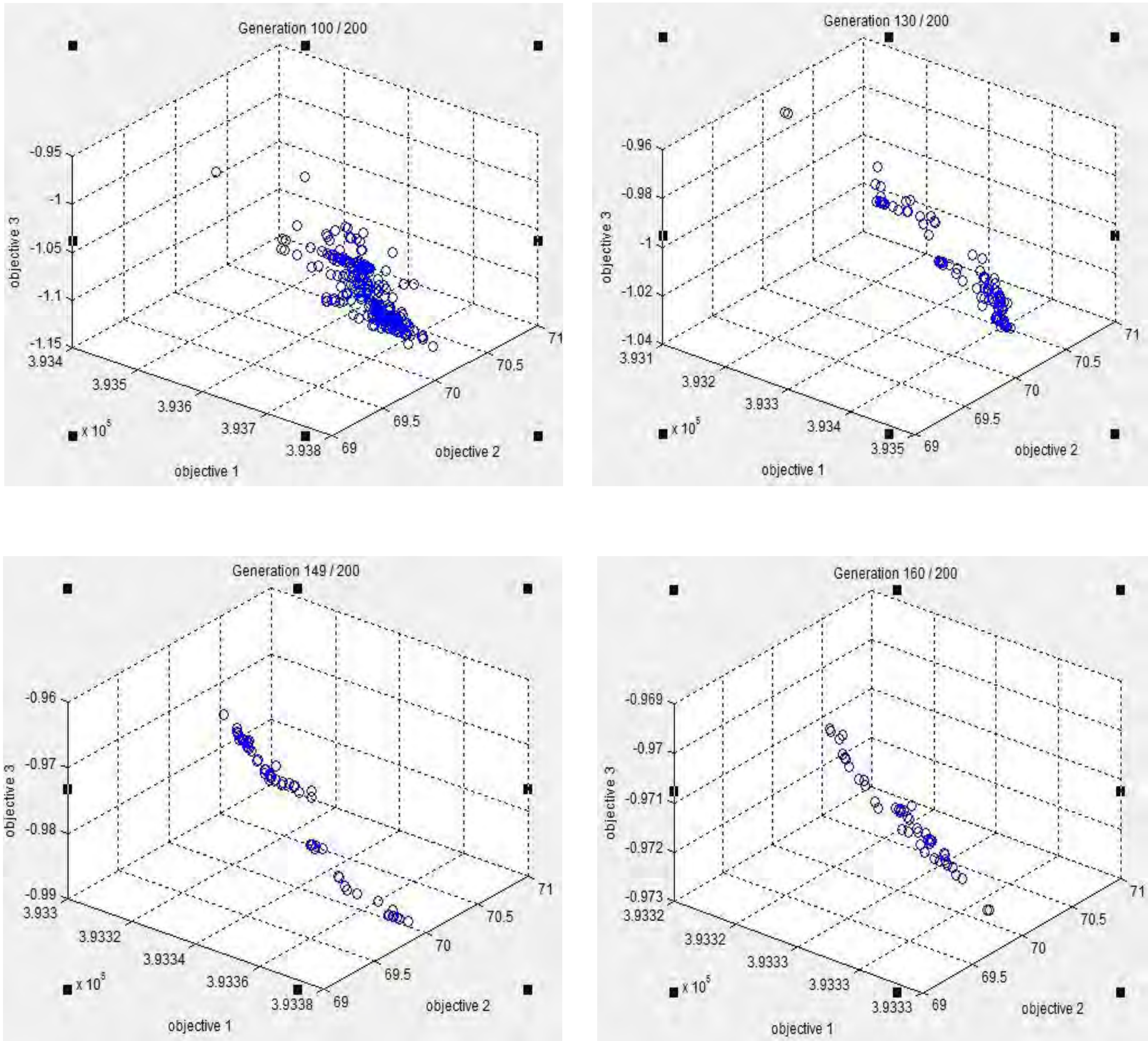


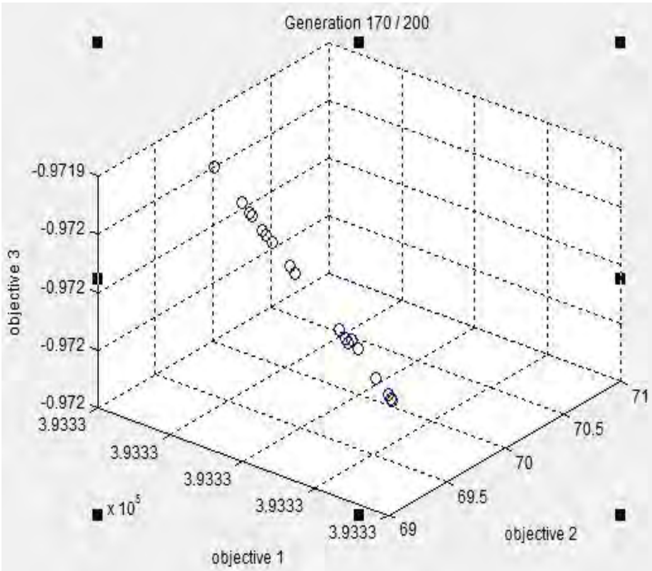

**Range of the value of Service level function**

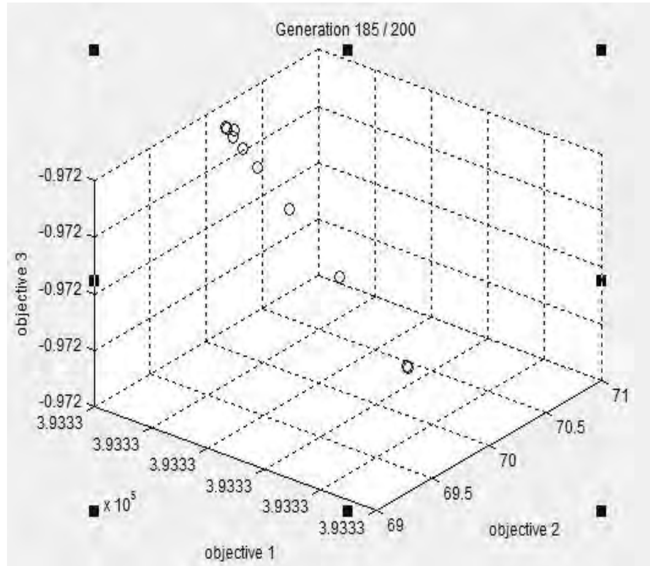
| Objective Function | Range | |
|---|---|---|
| | Minimum Value | Maximum Value |
| Customer Service Level Function, f3 | 0.944655 | 5.30167 |

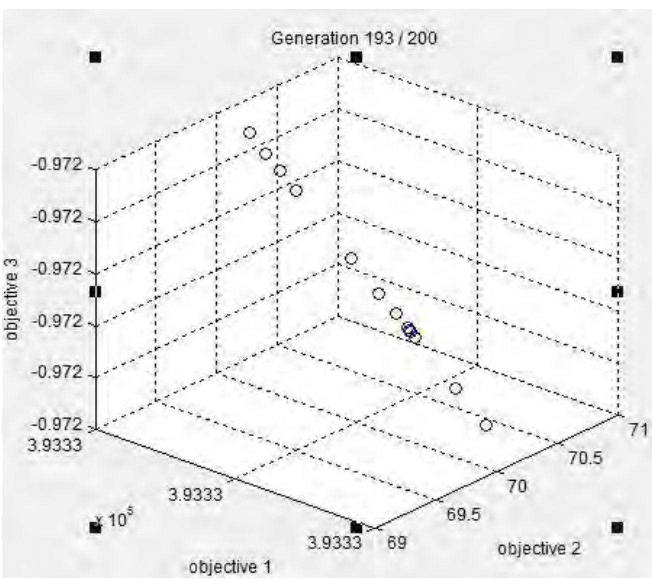


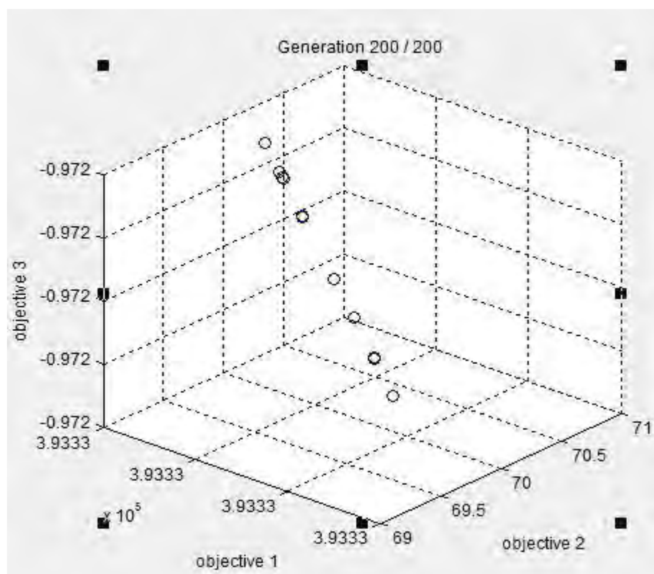
## Illustration of different pareto font for different generations




Generation 170 / 200
objective 3
-0.9719
-0.972
-0.972
-0.972
-0.972
3.9333
3.9333
3.9333
3.9333
3.9333
x 10^5
objective 1
69
69.5
70
70.5
71
objective 2


Generation 185 / 200
objective 3
-0.972
-0.972
-0.972
-0.972
-0.972
3.9333
3.9333
3.9333
3.9333
3.9333
x 10^5
objective 1
69
69.5
70
70.5
71
objective 2


Generation 193 / 200
objective 3
-0.972
-0.972
-0.972
-0.972
-0.972
-0.972
3.9333
3.9333
3.9333
x 10^5
objective 1
69
69.5
70
70.5
71
objective 2


Generation 200 / 200
objective 3
-0.972
-0.972
-0.972
-0.972
-0.972
3.9333
3.9333
3.9333
3.9333
x 10^5
objective 1
69
69.5
70
70.5
71
objective 2