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Integrated Optimization Models and Strategies for Green Supply Chain Planning

by

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An Abstract of

Integrated Optimization Models and Strategies for Green Supply Chain Planning

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The main goal of this research is to present new efficient methods and optimization models to enhance the Green Supply Chain Planning (GSCP). As a first objective, we focus on developing a novel optimization planning model in a green supply chain network consisting of suppliers, assemblers, distribution centers, and retailers. This model is subjected to various constraints which are related to the inventory and forward logistics management. We applied the proposed model for a vacuum and floor machines manufacturer case study located in the Midwestern, U.S. The main objective functions include: minimizing the costs of assembling, transporting, holding inventory at assembling sites and distribution centers, and shortage at retailers under carbon dioxide (CO_2) emissions constraints throughout the logistic network; maximizing service levels and determining the acceptable service levels to meet final customers' demands. We applied three different solution methods including a gradient-based algorithm in MATLAB "Find Minimum of Constrained nonlinear multivariable function (FminCon)", a novel metaheuristic algorithm "Grey Wolf", and the "Branch and Bound (B&B)" algorithm in Lingo to find optimal solutions for the proposed optimization model, which

has a specific complexity. We compared the achieved optimal solutions by these methods. The case study and expanded numerical example verify whenever the parameter of the minimum service level at retailers' sites increases or decreases, the amount of produced CO_2 emissions and the total costs of the supply chain will directly correlate. It also demonstrates the trade-offs among the total costs of the supply chain network, CO_2 emissions, and service levels. The achieved results reflect the efficiency of the proposed model for GSCP. As a second objective, we concentrate on revealing more information about optimal points in which performance measures of various adaptive $\overline{X}$ quality control charts hold their optimal minimum values. In this way, better quality control systems can be applied to detect defective parts and errors sooner, reduce the wastes, and find the related causes for the various processes involved in supply chain networks/production systems in order to achieve more effective GSCP and improve the quality control. Previous researches applied a forward viewpoint and evaluated the performance of adaptive models only for a specific and limited set of design parameters. However, in this research, we use a reverse perspective and search all possible sets of design parameters in the response space to find optimal minimum values for three performance measures, including adjusted average time until signal, average number of observations to signal, and average number of samples to signal. For this purpose, similar to recent studies, the Markov-chain approach is applied to develop performance measures. Then, a coded algorithm is proposed that explores the entire response surface and evaluate the value of each performance measure to find the optimal points. As an output, this algorithm obtains sets of initial parameters resulting in optimal minimum values of performance measures for adaptive models with respect to broad ranges of shifts in mean. It also computes the values of other performance measures and their improvement percentages in comparison to a fixed parameters control chart at obtained optimal points. The presented new guideline provides decision makers and quality managers with more knowledge about optimal points to choose a proper adaptive model, select an appropriate performance measure, and set economical and viable values for design parameters for specific ranges of shifts in mean that are estimated to have a higher priority in their process control. Finally, the third objective of this research is to evaluate the waste streams and recycling opportunities for various echelons of a supply chain. A real case study categorized in health care systems is considered for this purpose.

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List of Abbreviations

GSCP..........................Green Supply Chain Planning

NGOs ....Non-Governmental Organizations

PSO ....Paticle Swarm Algorithm

GA..............................Genetic Algorithm

GHG...........................GreenHouse Gas

B&B ....Branch and Bound

DC..............................Distributiob Center

MINLP ....Mixed Integer Non-Linear Programming

FminCon ....Find Minimum of Constrained nonlinear multivariable function

KKT ....Karush-Kuhn-Tucker

BWRAP ....Business Waste Reduction and Auditing Program

MIME.........................Mechanical, Industrial, and Manufacturing

SPC ....Statistical process control

FP ....Fixed Parameters

VSS ....Variable Sample Size

VSI ....Variable Sampling Interval

EPA............................United States Environmental Protection Agency

VSC............................Variable Sample Control limit

VSSI...........................Variable Sample size and Sampling Interval

VSIC ....Variable Sample Interval and variable sample Control limits

VSSC..........................Variable Sample Size and variable sample Control limits

VP ....Variable Parameters

ANOS.........................Average Number of Observations to Signal

ANSS ....Average Number of Samples to Signal

ATS ....Average Time out-of-control until a Signal

AATS ....Adjusted Average Time out-of-control until a Signal

MATS ....Mean of the Average Time to Signal

ANSW........................Average Numbers of SWitches between different values of design parameters made in in-control state

WHO..........................World Health Organization

IF................................Intuitionistic Fuzzy

WARM.......................WAste Reduction Model

MTCE ....Metric Tons of Carbon Equivalent

MSW..........................Municipal Solid Waste

IFWA ....Intuitionistic Fuzzy Weighted Averaging operator

ASWR........................Average SWitching Rate

SDTS..........................Standard Deviation of the Time to Signal

AEQL.........................Average Extra Quadratic Loss

ARL............................Average Run Length

SDRL ....Standard Deviation of the Run Length distribution

MCDM.......................Multi-Criteria Decision Making

AHP............................Analytic Hierarchy Process

DEMATEL ....DEcision-MAking Trial and Evaluation Laboratory

IFSs ....Intuitionistic Fuzzy Sets

List of Symbols

u ....Index of different types of components required for finished products

i ....Index of various finished product

j ....Index of suppliers

k ....Index of assemblers

k' ....Set of assemblers' sizes, in ft^2 (indexed by k')

w ....Index of distribution centers

w' ....Set of distribution centers' sizes, in ft^2 (indexed by w')

r ....Index of retailers

t ....Index of periods

m ....Number of suppliers

n ....Number of assemblers

q ....Number of distribution centers

v ....Number of retailers

a ....Number of components

p ....Number of products

T ....Number of periods

θ ....Average expected cost of carbon credits (in \$/tons CO_2)

$CO_2^{Allowed}$ ....The maximum amount (in tons) of carbon dioxide (CO_2) that can be emitted (assigned by government)

$CC_{k,w}$ ....Distance, in miles, between an assembler in location k and a distribution center in location w

$CC_{w,r}$ ....Distance, in miles, between a distribution center in location w and retailer in location r

$CC_{j,k}$ ....Distance, in miles, between a supplier in location *j* and an assembler in location *k*

∂_i ....The fixed cost of transportation related to product type *i* per unit distance

∂_u ....The fixed cost of transportation related to component type *u* per unit distance

$hw_{i,w}$ ....Unit inventory holding cost of i^{th} product at w^{th} distribution center's site per unit time

Ar_k ....Size in ft^2 of an assembling center *k*

Ar_w ....Size in ft^2 of a distribution center *w*

μ_o ....CO_2 emission factor of a facility, in tons per kWh of operation

μ_{tr} ....CO_2 emission factor for transportation, in tons per mile

E_k ....Energy requirement for an assembler of size k, in kWh per ft^2

E_w ....Energy requirement for a distribution center of size *w*, in kWh per ft^2

$D_{i,r,t}$ ....Demand of i^{th} product at r^{th} retailer's site occurred in t^{th} period

$F_{u,i}$ ....Coefficient of consumption related to u^{th} component in i^{th} product

$\pi r_{i,r}$ ....Unit backorder cost of i^{th} product at r^{th} retailer's site

$\tau_{i,k}$ ....The fixed cost of assembling of i^{th} product at k^{th} assembler's plant

$Cpr_{i,k}$ ....The unit cost for a regular time of assembling i^{th} product at k^{th} assembler's plant

$\rho_{u,i,k}$ ....The unit customization cost of u^{th} component in assembling i^{th} product by k^{th} assembler

$Tpr_{i,k,w}$ ....The unit transportation cost of i^{th} product carrying from k^{th} assembler to w^{th} distribution center

$\varphi_{i,r}$ ....Set-up cost of i^{th} product at r^{th} retailer's site per order by final customers

$Trw_{i,w,r}$ ....The unit transportation cost of i^{th} product carrying from w^{th} distribution center to r^{th} retailer

$CTrw_{i,w,r}$ ....Capacity limits to ship i^{th} product from w^{th} distribution center to r^{th} retailer

$CTrp_{i,k,w}$ ....Capacity limits to ship i^{th} product from k^{th} assembler to w^{th} distribution center

$Stw_{i,w}$ ....Storage capacity of i^{th} product at w^{th} distribution center

$G_{i,k}$ ....Maximum capacity for assembling i^{th} product at k^{th} assembler's site

$SL_{i,r,t}^{min}$ ....Minimum desired service level of i^{th} product at r^{th} retailer's site in t^{th} period

$hu_{u,k}$ ....The unit inventory holding cost of u^{th} component at k^{th} assembler's site per unit time

O_j ....Ordering set-up cost of j^{th} supplier

$S_{u,j}$ ....Unit selling price of u^{th} component offered by j^{th} supplier to assembler

$CS_{u,j}$ ....Capacity of providing u^{th} component at j^{th} supplier's site

$MI_{u,k,t}$ ....Maximum holding capacity of u^{th} component at k^{th} assembler's site in t^{th} period

$CO_2^{Emissions}$ ....The amount of CO_2 in tons that is currently emitted

$X_{i,k,t}$ ....The amount of produced units which is related to the i^{th} product at k^{th} assembler's site in t^{th} period

$BR_{i,r,t}$ ....The amount of i^{th} product backordered by r^{th} retailer in the end of t^{th} period

$V_{i,k,w,t}$ ....The amount of units which is related to the i^{th} product delivered from k^{th} assembler to w^{th} distribution center in t^{th} period

$Q_{i,w,r,t}$ ....The amount of units which is related to the i^{th} product dispatched to r^{th} retailer by w^{th} distribution center in t^{th} period

$Z_{u,j,k,t}$ ....The amount of units which is related to the u^{th} component, ordered by k^{th} assembler from j^{th} supplier in t^{th} period

$SL_{i,r,t}$ ....Desired service level at r^{th} retailer 'site related to i^{th} product in t^{th} period

$IW_{i,w,t}$ ....The amount of inventory related to i^{th} product at w^{th} distribution center's site in the end of t^{th} period

$IU_{u,k,t}$ ....The amount of inventory related to u^{th} component at k^{th} assembler's site in the end of t^{th} period

$\alpha_{i,r,t}$ ....Binary variable and if r^{th} retailer places assembly order for i^{th} product in t^{th} period, its value is 1

$\beta_{i,k,t}$ ....Binary variable and if assembling of i^{th} product at k^{th} assembler's plant has been set up in t^{th} period, its value is 1

$\delta_{w,r}$ ....Binary variable and if r^{th} retailer places order to w^{th} distribution centers, its value is 1

$\gamma_{k,w}$ ....Binary variable and if w^{th} distribution center places an order to k^{th} assembler, its value is 1

$Y_{j,k,t}$ ....Binary variable and if k^{th} assembler places order to j^{th} supplier in t^{th} period, its value is 1

Chapter 1

1 Introduction

Concerns about manufacturing and supply chain consequences on the natural environment have been rising for decades. Carbon footprint analysis and control of greenhouse gas emissions have become more relevant concepts and necessary practices. As the world population grows drastically, resources are further strained. Given this situation, finding systematic ways to sustain our resources and surrounding environments seems critical. Various instruments alternating from taxes, permits, and voluntary incentives to requisite regulatory policies are employed by governments to cope with climate change and greenhouse gas emissions. In regards to this issue, Green Supply Chain Planning (GSCP) is one of the most essential decisions in today's global market. Companies prefer to gain a competitive advantage by emphasizing their attention on the entire supply chain and successful establishment of an environment-friendly planning. Currently, industry practitioners and policy makers are under an increasing amount of pressure to constantly reduce the negative environmental impact of their supply chains. GSCP, an effective method for promoting the environmentally friendly management of supply chain activities from beginning to end, has the ability to reduce waste, minimize pollution, save energy, conserve natural resources, and control carbon emissions (Min and Kim, 2009; Badkoobehi *et al.*, 2011; Seyedhosseini *et al.*, 2011; Ageron *et al.*, 2012; Elahi and Franchetti, 2013; Akhavan *et al.*, 2014; Kusi-Sarpong *et al.*, 2014; Garg *et al.*, 2015; Giri, *et al.*, 2015; Soleimani and Kannan, 2015; Elahi and Franchetti, 2015a). GSCP can be described as a coordination tool of the supply chain in a form that integrates environmental concerns and reflects the inter-organizational activities. GSCP copes with the acquisition, production and distribution of materials to meet the requirements of stakeholders to enhance profitability, competitiveness and the resilience of the suppliers, manufacturing system, distribution centers, and retailers in the short and medium terms through advanced green performance (Ahi and Searcy, 2013). Improvements by GSCP can be categorized as follows (Franchetti *et al.* (2016a, 2016b):

- Operations improvement: GSCP improves the operations by incorporating environmental and waste managerial solutions.
- Agility enhancement: GSCP helps mitigate risks and speed innovations.
- Adaptability improvement: GSCP analysis often leads to innovative processes and continuous improvements.
- Alignment improvement: GSCP involves negotiating policies with suppliers and customers, which results in better alignment of manufacturing processes and principles.

1.1 Objectives and Scope

In the context of the limitations of previous research (Amin and Zhang, 2013; Shankar *et al.*, 2013; Kannan *et al.*, 2013; Fahimnia *et al.*, 2015a; Hsueh, 2015; Coskun *et al.*, 2015; Wu and Chang, 2015; Rodrigues *et al.*, 2015; Sazvar *et al.*, 2014; Govindan *et al.*, 2014; Subulan *et al.*, 2014), the objective of this dissertation is to present new efficient methods and optimization models to enhance the GSCP. For this purpose, we focus on three different perspectives based on studied real cases (Figure 1-1). As a first viewpoint, we concentrate on proposing a multi-objective optimization model which minimizes total costs under CO_2 emissions constraints, controls inventory, and maximizes service levels concurrently. Such a novel integrated optimization provides a tradeoff model between costs, CO_2 emissions, and service levels for GSCP. As a second viewpoint, our focus is on improving quality control in various processes integrated with the GSCP in order to minimize the amount of defective products and scraps. To achieve this outcome, we present a new statistical guideline using adaptive $\bar{\boldsymbol{X}}$ control charts. As a third perspective, we focus on evaluation of waste streams and recycling opportunities for various echelons of a supply chain. A real case study categorized in health care systems is presented and analyzed in that section.

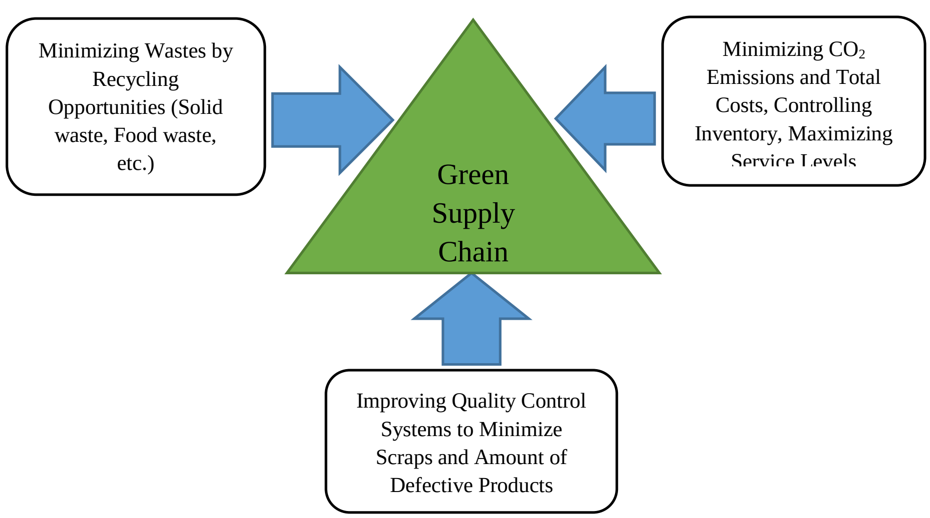

Figure 1-1: Overview of three major perspectives (focus areas) considered in this dissertation

1.2 Dissertation Contributions

The main objective of this dissertation is to develop new effective optimization methodologies, models, and strategies for GSCP. The proposed methods and models in this research can be applied by various supply chain coordinators, production and operations managers, manufacturers, and producers.

1.3 Outline of the Dissertation

The dissertation is divided into six chapters. In chapter 2, a literature review on the GSCP models and frameworks are presented. This chapter also includes the definition of the problem and the significance of the research, objective and scope, and major contributions of the research. In chapter 3, as a first primary research work of this proposal, a new optimization model for the GSCP by focusing on objectives containing: minimization of total costs under CO_2 emissions constraints, and maximization of service levels is presented and discussed. We have expanded the data of a real case study for this proposed model. In chapter 4, as a second primary research work of this proposal, a new statistical guideline using adaptive $\bar{X}$ control charts for a better quality control of processes involved in a GSCP procedure is proposed and analyzed. In chapter 5, as a third primary research work of this dissertation, we focus on solid waste stream assessment and recycling opportunities to decrease solid wastes in a supply chain. For this purpose, real data of a health care system is applied. In chapter 6, a summary of the study is presented and some ideas for future research are suggested.

Chapter 2

2 Literature Review

As mentioned in chapter 1, GSCP has received great interest from practitioners and scholars in recent years due to pressure from various stakeholders, including consumers, community activists, NGOs, governmental legislation, and global competition. The need to sustain supply chains has resulted in many companies selecting a certain level of commitment in their sustainability practices. Academia and various industries of the global economy have implemented triple bottom line and sustainability initiatives such as energy efficient technologies, the use of renewable sources, recycling, green procurement, reduced packaging, carbon emission accounting, social responsibilities, and employee recognition to ensure sustainability and environmental aspects in supply chain planning. In GSCP, environmental and social criteria require to be fulfilled by the members to remain within the supply chain, whereas it is expected that competitiveness would be maintained through meeting customer's needs and associated economic criteria. GSCP concept has been come into sight in the last few years. Combining the 'green' concept with the 'supply chain planning' notion establishes a novel paradigm where the supply chain planning will have a direct relationship with the environment. This is noteworthy since historically, these two paradigms have been in conflict with each other (Srivastava, 2007; Seuring and Müller, 2008).

A comprehensive network analysis literature review on GSCP researches was presented by Fahimnia *et al.* (2015b). Based on their findings, the geographic dispersion of the research works did signify that Europe, though with few highly influential publications, seemed to have the greatest number of works, with North America not far behind. The diffusion of the work into Asia is also starting to take place. They observed, using an objective clustering approach, that conceptual and empirical studies have set the foundation and represent the most influential works. Their topical literature classification also demonstrated that prescriptive and quantitative modeling has begun to take on greater importance.

A review of recent literature indicates that multiple research studies have focused on GSCP by considering various assumptions and utilizing different methodologies and solution methods entailing Gradient-based algorithms (Hsueh, 2015), Meta-heuristics methods such as PSO (Shankar *et al.*, 2013), GA (Yeh and Chuang, 2011), Hybrid meta-heuristics algorithms such as the integration of GA and PSO (Soleimani and Kannan, 2015), Hybrid solution methods integrating simulation with a meta-heuristic search method such as a simulation-based hybrid variable neighborhood search (Zolfagharinia *et al.*, 2014), Compromise programming (Elahi *et al.*, 2011a; Elahi and Franchetti, 2012; Sazvar *et al.*, 2014), Fuzzy programming (Nie *et al.*, 2009; Kannan *et al.*, 2013; Subulan *et al.*, 2014; Kusi-Sarpong *et al.*, 2014,), Goal Programming (Coskun *et al.*, 2015), Scenario development and scenario analysis (Coskun *et al.*, 2015; Rodrigues *et al.*, 2015; Amin and Zhang, 2013), Stochastic programming (Mirzapour *et al.*, 2013; Amin and

Zhang, 2013), Game theory (Zhang and Liu, 2013), Simulation such as Monte Carlo (Mangla *et al.*, 2014), and Multi-Criteria Decision Making (MCDM) (Subulan, *et al.*, 2014; Wu and Chang, 2015; Kusi-Sarpong *et al.*, 2014). Nie *et al.* (2009) developed an interval fuzzy robust dynamic programming model for the GSCP issue considering waste-flow allocation and treatment/disposal facility in situations with highly complex and uncertain information.

Kusi-Sarpong *et al.* (2014) introduced a comprehensive framework for green supply chain practices in the mining industry. They applied a multiple criteria evaluation of green supply programs using a novel multiple criteria approach that integrates rough set theory elements and fuzzy TOPSIS for weighting schemes of defined factors.

This study identified six distinctive green supply chain practices and sub-practices that include green information technology and systems, strategic supplier partnership, operations and logistics integration, internal environmental management, eco-innovative practices, and end-of-life practices. Yeh and Chuang (2011) developed a mathematical model for optimal planning in a supply chain network and choosing green partners by using GA. Zhang and Liu (2013) applied Game theory in view of the three-level green supply chain system, where market demand is associated with the environmentally friendly products. Their findings showed that the profits of both the supply chain system and participating members get to the optimal level under cooperative decision-making. The decision results of contributing members along with the channel profit are far from satisfactory under the non-cooperative game. By defining the cooperative parameter, green supply chain managers may efficiently get involved in coordination mechanisms to intervene and adjust the green channel to promote the smooth operation of a green supply chain.

Mirzapour *et al.* (2013) propositioned a stochastic programming approach to solve a multi-period, multi-product, multi-site aggregate production-planning problem in a green supply chain network for medium-term planning. Mangla *et al.* (2014) focused on the operational green supply chain risk evaluation. They applied Monte Carlo simulation to evaluate the related risks. They considered five operational risks containing: machine/ equipment /facility failure, process design risks, lack of skilled labor, green technology level inadequacy, a system/software failure. They analyzed their consequences in terms of time, brand image, economic, health and safety, and quality. Based on their findings, the maximum consequences were seen in time-based consequences and that was measured in terms of time delays/disturbances and disruptions. Coskun *et al.* (2015) focused on supply chain network design based on defined green expectations of consumer and the retailer's general expectations from candidate suppliers (i.e. manufacturers, carriers and distribution centers on the network). They proposed a goal-programming model considering three consumer segments, i.e., green, inconsistent and red consumers. Green consumer segment defines consumers who demand green products for sure and willing to pay extra for them. The second segment defines inconsistent consumers who have some level of awareness towards the environment, yet they prefer a green product only if the price is same or less above the price of alternative non-green one. Third segment hosts red consumers who do not pay any attention to products' greenness and make up his/her purchasing decision based on other commonly used criteria. A set of scenarios was also studied to offer an insight on how the consumer determination level of greenness affects the green supply network. The ultimate goal of this study was to increase the market share of green products by managing the network to offer products with the expected greenness level determined by the consumer without ignoring profitability.

The literature review also indicates that the conducted researches on GSCP incorporate three aspects of sustainability and green programs: social aspect (Hsueh, 2015), environmental aspect (Sazvar *et al.*, 2014; Kannan *et al.*, 2013; Govindan *et al.* 2013; Coskun *et al.*, 2015; Rodrigues *et al.*, 2015; Amin and Zhang, 2013; Wu and Chang, 2015; Kusi-Sarpong *et al.*, 2014), and economical aspect (Seyed-Hosseini *et al.* 2010a,b; Elahi *et al.*, 2011b,c,d,e; Shankar *et al*., 2013; Subulan *et al*., 2014; Yang *et al.*, 2009; Wu and Chang, 2015; Soleimani and Kannan, 2015; Zolfagharinia *et al.*, 2014; Kusi-Sarpong *et al*., 2014).

Pishvaee *et al.* (2012) focused on assessing and controlling emissions across the logistics network. They proposed a bi-objective credibility-based fuzzy mathematical programming model for designing the strategic configuration of a green logistics network under uncertain situation. The model aimed to minimize the environmental impacts and the total costs of network establishment concurrently for the sake of offering a practical balance. Zhao *et al.* (2012) proposed an approach, in the context of GSCP, using Game theory to examine the strategies chosen by manufacturers to diminish life cycle environmental risk of materials and carbon emissions. They attempted to establish a base for determining the extent of environmental risk and carbon emissions reduction within the application of the ‘tolerability of risk’ notion. Kannan *et al.* (2013) presented an integrated approach of fuzzy multi attribute utility theory and multi-objective programming for rating and selecting the best green suppliers, according to economic and environmental criteria and then allocating the optimum order quantities among them. They also proposed a mathematical model to maximize the total value of purchasing and to minimize the total cost of purchasing. Govindan *et al.* (2013) proposed a multi-objective optimization model by integrating sustainability in decision-making on distribution in a perishable food supply chain network. They focused on a location–routing problem with time-windows. Shankar *et al.* (2013) focused on optimization of strategic design and distribution decisions in a supply chain network by minimizing the combined facility location, production, inventory, and shipment costs and maximizing fill rate. Kannegiesser and Gunther (2013) applied an optimization strategy to set long-term sustainability targets for supply chain based on defined performance indicators, e.g. CO_2 emissions, waste, energy and water consumption reduction, and cost reductions. The main characteristic of such a strategy was setting concrete targets for different dimensions of sustainability. The overall objective consisted of minimizing the number of periods required until all of the targets are reached.

Sazvar et al. (2014) proposed a new replenishment policy in a centralized supply chain for deteriorating items. The best transportation vehicles and inventory policy were determined by finding a balance between financial and environmental criteria. They concentrated on minimization of expected total costs and expected GHG emissions. The results verified that if companies allow a minor reduction in the system’s profits, they will be able to improve their GHG criteria significantly. Zolfagharinia et al. (2014) developed a two-stock inventory control model for a reverse supply chain with separate serviceable and remanufacturable inventory stock points. They considered the dependency of product return and market demand in presence of product life cycle in a two-stock system with backordering option. The objective of incorporating a remanufacturable stock point was to take advantage of low holding cost for storing inexpensive returned products and postponing the remanufacturing process to the time when needed. To model demand pattern during product life cycle, they introduced an order-up-to replenishment policy with five maximum inventory levels corresponding to five product life cycle stages including introduction, growth, maturity, saturation, and decline stages. A hybrid solution method was developed through integrating discrete event simulation with a meta-heuristic algorithm to find a near-optimum solution for the proposed inventory control problem. Shafii *et al.* (2011) focused on minimizing CO_2 and NOx emissions in automobile industry and conducted various experimental tests to investigate the effects of adding water-based Ferro fluid to diesel fuel in a diesel engine. They found that adding Ferro fluid to diesel fuel has a significant effect on engine performance, increasing the brake thermal efficiency relatively up to 12% and decreasing the brake-specific fuel consumption reasonably up to 11% as compared to diesel fuel. Moreover, this research paper presented the idea of collecting nanoparticles at the exhaust flow using a magnetic bar.

Hsueh (2015) proposed a bi-level programming model to maximize total supply chain profits by determining optimal performance levels of corporate social responsibility. They used linear inverse demand functions to reflect the impact of corporate social responsibility performance on market prices. They showed that in some circumstances, the supply chain's profits and the individual profits of each supply chain actor can be improved by corporate social responsibility collaboration.

Rodrigues *et al.* (2015) conducted a study on assessing possible carbon mitigation strategies for UK supply chains by using a combination of alternative ports and revised multi-modal strategies. They considered whether the use of alternative port gateways can contribute significantly to an overall reduction in freight transport-related CO_2e[1] emissions in international supply chains. An activity-based CO_2e emission model is used to estimate the cost and CO_2e impact of five Scenarios which are described in the paper as the ''current situation'' and four ''proposed Scenarios''. The Scenarios modelled in their research paper included a baseline scenario and a series of scenarios which captured the outcomes when alternative routes were used. The proposed model assessed the tradeoffs between CO_2e reduction in road freight transport and modal shift from road to water and/rail. A range of variables which can impact on the overall cost and CO_2e emissions were: terminal building costs, transport operating costs, intermodal freight transfer cost, and CO_2e emissions derived from the use of alternative modes and routes. The aim of the modelling process was to achieve an understanding of how UK import containers may potentially be re-routed such that either costs or CO_2e emissions, or both, could be reduced. The overall aim of their study was to simulate possible CO_2e mitigation strategies along supply chains in the UK.

Wu and Chang (2015) identified the critical dimensions and factors for electrical and electronic industries and constructed the digraphs to show causal relationships among

[1] CO_2e, or carbon dioxide equivalent, is a standard unit for measuring carbon footprints

dimensions and factors within each dimension in a green supply chain network. Four different dimensions were considered: supplier management (factors: environmental auditing for suppliers, supplier environmental questionnaire, requesting compliance statement, asking for product testing report, demanding bill of material, establishing environmental requirements for purchasing items, implementing green purchasing), Product recycling (factors: joining local recycling organization, collaboration on products recycling with the same sector industry, produce disassembly manual), Organization involvement (factors: green design, top management support, environmental policy for green supply chain management, cross-function integration, manpower involvement, effective communication platform within companies and with suppliers, establish an environmental risk management system for green supply chain management, supplier evaluation and selection), and Life cycle management (factors: applying life cycle assessment to carry out eco-report and establish an environmental database of products). The results showed that organization involvement is the most critical dimension. Moreover, top management support and environmental policy for green supply chain network are the two critical factors in organization involvement that should be placed in highest priority when green supply chain network is to be implemented.

Several recent studies have also focused on closed-loop supply chains. Yang *et al.* (2009) expanded the research work of Hammond and Beullens (2007) and combined the research work of Sheu *et al.* (2005) to develop a general closed-loop supply chain network, which consists of raw material suppliers, manufacturers, retailers, consumers and recovery centers. They optimized the equilibrium state of the network by using the theory of variational inequalities and the equilibrium condition. Wang and Hsu (2010) examined the integration of forward and reverse logistics with a simplified closed-loop model for the logistical planning. They formulated a cyclic logistics network problem into an integer linear programming model. They utilized a revised spanning-tree based genetic algorithm that was extended by using a determinant encoding representation for solving their proposed model. Amin and Zhang (2013) proposed a stochastic programming model to minimize the total cost and maximize the recycling and use of clean energies like a solar power by collection centers to process products in a closed-loop supply chain. Elahi and Franchetti (2014) also proposed a comprehensive conceptual model for a closed-loop supply chain and considered product life cycle and three types of returns into account. In this conceptual model, once products are applied by final customers, some of them are returned back. The returning products are delivered to the collection site. Commercial returns are fixed at the repair site. These products can be utilized as new ones. End-of-use and end-of-life returns are disassembled. In this phase, the wastes are separated. End-of-life returns are recycled at recycling sites. It is also assumed that the parts are added to the part inventory as new parts. Subulan *et al.* (2014) developed a multi-objective, multi-echelon and multi-product strategic planning model for the lead/acid battery closed-loop supply chain. They focused on three objectives: a) minimizing the total cost: summation of fixed opening costs, production costs, transportation costs, component purchasing costs, scrap battery purchasing costs, recycling costs, collection costs, disposal costs minus revenue obtained from the sales of collected scrap batteries, b) maximizing the coverage of collected batteries by opened collection centers or hybrid facilities, and c) maximizing the total volume flexibility which consists of manufacturing or plant volume flexibility, distribution volume flexibility, recycling volume flexibility and collection volume flexibility. Soleimani and Kannan (2015) coped with a closed-loop supply chain design and planning problem through a deterministic approach by maximizing the profit. Various cost including fixed opening costs, material supplying costs, manufacturing costs, non-utilized capacity costs, shortage costs, purchasing costs of return products from customers, disassembly costs of return products, recycling costs, remanufacturing costs, repairing costs, disposal costs, transportation costs, and inventory holding costs were considered. Garg *et al.* (2015) focused on the environmental issues presented in the design of closed-loop supply chain networks. In the reverse chain of the proposed closed-loop supply chain network, returned products were collected from their users through a take back scheme. Users were paid incentives for returning their end-of-life used products at the company operated collection center. Value was recovered by dismantling returned products into the components demanded in the spare market.

Some of recent researches in the area of GSCP are categorized in Table 2.1 based on various elements containing type of model, the number of objective functions, focus on profit /cost of supply chain network, number of echelons in the supply chain network, and considered decision variables. These researches are also clustered based on the use of numerical example/case study, applied methodology and solution Method, deterministic/stochastic/fuzzy Model, deterministic/probabilistic demand, single/multi-period, and single/multi-product. Such a clustering is displayed in Table 2.2. Various considered scopes in decisions for the Green Supply Chain Planning (i.e. production or manufacturing’s capacity; supplier’s capacity; Distribution center’s capacity; Collection center’s capacity; Wholesaler’s capacity; Recycling capacity; Transportation capacity;

Inventory; performance evaluation; procurement and order allocation; production and operation; transportation, shipment, and logistics management; sustainability and green aspects; facility location; partial back-ordering; routing) are also classified in Table 2.3.

However, all the aforementioned research focused on various issues in the context of GSCP, the trade-offs between minimizing total costs (i.e. carbon emission costs, transportation costs, holding costs of inventory, fixed ordering costs, costs of purchase, assembly costs, and backordering costs of products) and maximizing service levels in a multi-sourcing situation with multi-product and multi-period have not been taken into consideration. The first goal of this research is to develop a novel optimization planning model in a green supply chain network consisting of suppliers, assemblers, distribution centers, and retailers. This model is subjected to various constraints which are related to the inventory and forward logistics management and carbon dioxide (CO_2) emissions throughout the logistic network. The proposed model for supply chain network is applied in a vacuum and floor machines manufacture case study in the Midwest. The main objectives considered are: a) minimizing the costs of assembling, transporting, holding inventory at assembling sites and distribution centers, and shortage at retailers; and b) maximizing service levels. The model can determine the acceptable service levels to meet final customers' demands. Moreover, as the proposed nonlinear optimization model has specific complexity, optimality is achieved by three different solution methods. In the first step, an optimization solver, the B&B solver, is utilized to achieve an initial local optimum solution. In the second step, a gradient-based programing solver is applied to achieve the best solution. In the third step, a metaheuristic algorithm (Grey Wolf Optimizer algorithm) is applied to achieve optimality. The case study and expanded numerical example verify that whenever the parameter of the minimum service level at retailers' sites increases or decreases, the amount of produced CO_2 emissions and the total costs of the supply chain will directly correlate. The achieved results by the three different solution methods reflect the efficiency of the proposed model in the context of GSCP. The next chapter will focus on the proposed optimization model.

Table 2.1: Categorizing recent researches in the area of Green Supply Chain Planning based on considered objective and decision variables

Authors	**Model**	**Single objective/ Bi-objective/ Triple-Objective**	**Profit/ Cost**	**Echelons (Layers) in the Supply Chain Network**	**Decision Variables**
Hsueh (2015)	Bi-level programming model	single objective	Profit	Three echelons: suppliers, one manufacturer, and retailers	• Corporate social responsibility performance level of suppliers, the manufacturer, and retailers • Transaction quantity and compensations transferred between the supplier and the manufacturer/ the manufacturer and retailer
Shankar *et al.* (2013)	Bi-objective mixed-integer non-linear programming model	bi-objective	Cost	Three echelons: suppliers, production plants, and distribution centers (DCs)	• The number and location of plants in the system • The flow of raw materials from suppliers to plants • The quantity of products to be shipped from plants to distribution centers
Sazvar *et al.* (2014)	Linear mathematical model (multi-stage stochastic programming)	bi-objective	Cost	Two echelons; a supplier, a retailer	• The best configuration of vehicle types and order quantities in each period
Kannan *et al.* (2013)	Fuzzy Multi-objective linear programming	bi-objective	Cost	One echelon, multiple suppliers	• Selecting suppliers based on economic and environmental criteria • Assigning order quantity
Govindan *et al.* (2013)	Multi-objective mixed-integer programming	bi-objective	Cost	Three echelons, manufacturers, distribution centers, and retailers	• Determining the number and location facilities • Optimizing the amount of products delivered to lower stages and routes at each level • Finding the most efficient vehicle routes to minimize total costs and environmental effects of all three stages

Table 2.1 (cont.)

Authors	Model	Single objective/ Bi-objective/ Triple-Objective	Profit/ Cost	Echelons (Layers) in the Supply Chain Network	Decision Variables
Subulan *et al.* (2014)	Fuzzy Multi-objective linear programming	triple-objective	Cost	Five echelons: vendors (suppliers); manufacturers, regional wholesalers, dealers (retailers or authorized automotive services); potential licensed recycling facilities	• Recycling quantity of used battery at the licensed recycling facility • Quantity of used battery sold to any scrap dealer from each of depots (Hybrid facility or collection center) • Quantity of used battery purchased by each depot (Hybrid facility or collection center) from any scrap dealer and sent to the licensed recycling facility • Amount of material/component purchased from vendors • Production quantity of battery in new battery manufacturers • Quantity of battery shipped from new battery manufacturers via regional wholesalers or hybrid facilities to the battery dealers • Quantity of used battery shipped from battery dealers via collection centers or hybrid facilities to the licensed recycling facilities • Quantity of material/component shipped to new battery manufacturers from licensed recycling facilities
Coskun *et al.* (2015)	Goal-programming model	single objective	Profit	Two echelons: manufacturers and distribution centers	• Amount of demand to be fulfilled in stores for products and Lost sales amount for demands • Deviational variable for manufacturers for staying (and also exceeding) under expectations of segments • Deviational variable for manufacturers for staying (and also exceeding) under expectations of retailer • Deviational variable for carriers and distribution centers for staying (and also exceeding) under expectations of segments and retailers

Table 2.1 (cont.)

Authors	Model	Single objective/ Bi-objective/ Triple-Objective	Profit/ Cost	Echelons (Layers) in the Supply Chain Network	Decision Variables
Rodrigues *et al.* (2015)	Linear programming	single objective	Cost	One echelon: container handling and freight transport	• Number of units shipped from ports to references cities • Evaluating the demand allocation to rail transport and sea-based transport for specific scenarios
Amin and Zhang (2013)	Mixed-integer linear programming	bi-objective	Cost	Three echelons: multiple plants, collection centers, demand markets	• Quantity of products produced by plants for demand markets • Quantity of returned products from a) demand markets to collection centers, b) collection centers to plants, and c) collection centers to disposal centers
Yang *et al.* (2009)	Mathematical modeling and using the equilibrium condition	single objective	Profit	suppliers, manufacturers, retailers, consumers and recovery centers	• Each manufacturer must make several basic decisions: (a) how much of products to demand; (b) how much of raw materials to input; (c) how much of reusable materials to input. • The consumers take into account in making their decisions: (a) how much of the products to purchase from the retailers; (b) how much they will be willing to pay for the products; (c) how much of the used products willing to return to the recovery centers
Wu and Chang (2015)	A decision making method (MCDM)	single objective	none	three echelons: Suppliers, manufacturers, customers	• Ranking dimensions and finding the factors' effects
Soleimani and Kannan (2015)	Mixed-integer programming model	single objective	Profit	Multi-echelon: suppliers, manufacturers, warehouses, distributors, retailers, disassembly centers, redistributors, disposal centers	• Location and allocation variables

Table 2.1 (cont.)

Authors	Model	Single objective/ Bi-objective/ Triple-Objective	Profit/ Cost	Echelons (Layers) in the Supply Chain Network	Decision Variables
Zolfagharinia *et al.* (2014)	Mathematical modeling and simulation	single objective	Cost	three echelons: supplier, manufacturer, customer	• Demand in each period • Quantity of ordered products at the beginning of each period • Quantity of purchased products at the beginning of each period • Quantity of remanufactured products at the beginning of each period • Quantity of backordered items at the end of each period • Inventory position at the beginning of each period and On-hand inventory and Net stock at the end of each period • Quantity of products delivered to the market in each period
Kusi-Sarpong *et al.* (2014)	A decision making method	single objective	none	Not defined	• Ranking defined factors in evaluation of green supply programs
Garg *et al.* (2015)	Bi-objective integer nonlinear programming	bi-objective	Profit	Supplier, manufacturer, distribution center, customers, collection center, repair center, decomposition center, disposal site, dismantler, spare market	• Determining the optimal flow of parts and products in the closed-loop supply chain network and the optimum number of trucks hired by facilities in the forward chain of the network • Quantity of material shipped from suppliers to plants via trucks • Quantity of product shipped from: a) plants to distribution centers via trucks and b) distribution centers to customers via trucks • Quantity of used product returned from: a) customer market zones to collection centers and b) collection centers to dismantler center • Quantity of components shipped from: a) dismantler to repairing centers, b) repairing centers to spare markets, and c) dismantler to decomposition center • Quantity of material shipped from a) decomposition center to suppliers and b) decomposition center to disposal site • Number of various types of vehicles hired by suppliers and DCs.

Table 2.2: Clustering recent researches in the area of Green Supply Chain Planning based on applied methodologies

Authors	**Numerical example/ case study, the related industry**	**Methodology and Solution Method**	**Deterministic/ Stochastic/ Fuzzy Model**	**Deterministic /Probabilistic Demand**	**Single / Multi-period**	**Single /Multi-Product**
Hsueh (2015)	Numerical example	A gradient-based algorithm for sensitivity analysis of variation inequality models and bi-level programming	Deterministic	Deterministic	Single Period	Single Product
Shankar *et al.* (2013)	Case study, Pump manufacturing industry	A swarm intelligence based multi-objective hybrid particle swarm	Deterministic	Deterministic	Single Period	Single Product
Sazvar *et al.* (2014)	Case study, pharmaceutical industry with perishable products (radiopharmaceutical product)	Compromise programming	Stochastic	Stochastic	Multi-period	Single Product
Kannan *et al.* (2013)	Case study, automobile manufacturing company	Fuzzy Analytic Hierarchy Process, Fuzzy TOPSIS, Fuzzy Multi-objective linear programming converting to a single objective using a maxi-min formulation	Triangular fuzzy numbers	Deterministic	Single Period	Single Product
Govindan *et al.* (2013)	Numerical example	Hybrid algorithm based on multi-objective particle swarm optimization (MOPSO) and adapted multi-objective variable neighborhood search (AMOVNS)	Deterministic	Deterministic	Single Period	Single Product
Subulan *et al.* (2014)	Case study, lead/acid industry in Turkey	Fuzzy goal programming, weighted geometric mean for group decision making (MCDM)	Fuzzy	Deterministic	Single period	Multi-product

Table 2.2 (cont.)

Authors	Numerical example/ case study, the related industry	Methodology and Solution Method	Deterministic/ Stochastic/ Fuzzy Model	Deterministic /Probabilistic Demand	Single / Multi-period	Single /Multi-Product
Coskun *et al.* (2015)	Numerical example	Goal programming approach, scenario analysis	Deterministic	Deterministic	Single period	Multi-product
Rodrigues *et al.* (2015)	Case study, data related to different major container handling ports in UK (locations and container volume data for all routes analyzed in the five scenarios)	Scenario analysis	Deterministic	Deterministic	Single period	Single Product
Amin and Zhang (2013)	Numerical example based on a copier remanufacturing	Epsilon-constraint method; weighted sums method; stochastic programming (scenario-based)	Stochastic	Deterministic	Single period	Multi Product
Yang *et al.* (2009)	Numerical example	Mathematical modeling, using the theory of variational inequalities, and equilibrium conditions	Deterministic	Deterministic	Single period	Single Product
Wu and Chang (2015)	Case study, top five downstream suppliers in lead frames for the semiconductor packaging plants in Taiwan	MCDM method, DEMATEL (Decision-making trial and evaluation laboratory method)	Deterministic	Not considered	Not considered	Single Product

Table 2.2 (cont.)

Authors	**Numerical example/ case study, the related industry**	**Methodology and Solution Method**	**Deterministic/ Stochastic/ Fuzzy Model**	**Deterministic /Probabilistic Demand**	**Single / Multi-period**	**Single /Multi-Product**
Soleimani and Kannan (2015)	Case study, hospital furniture manufacturer	A hybrid algorithm: the genetic algorithm (GA) and particle swarm optimization (PSO)	Deterministic	Deterministic	Multi-period	Multi Product
Zolfagharinia *et al.* (2014)	Case study, Australian case company involved in the provision of toner cartridges	A hybrid solution method integrating a discrete event simulation with a meta-heuristic search method, Simulation-based Hybrid Variable Neighborhood Search	Deterministic	Stochastic	Multi-period	Multi Product
Kusi-Sarpong *et al.* (2014)	Case study, gathering data from mining engineers who work for Ghanaian mining industry	Integration of rough set theory elements and fuzzy TOPSIS	Fuzzy	Not considered	Not considered	Not considered
Garg *et al.* (2015)	Case study, gathering data from a geyser manufacturer Delhi and the National Capital Region	Interactive Multi-Objective Programming approach algorithm	Deterministic	Deterministic	Single period	Single product

Table 2.3: Various considered scopes in decisions for the Green Supply Chain Planning

Author	Production or Manufacturing capacity	Supplier (Vendor)'s capacity	Distribution center's capacity	Collection center's capacity	Wholesalers' capacity	Recycling capacity	Transportation capacity	Inventory	Performance evaluation	Procurement and order allocation	Production and operation	Transportation, shipment, and logistics management	Sustainability and Green aspects			Facility location	Partial Backordering	Routing
													Social aspect	Environmental aspect	Economic aspect			
Hsueh (2015)									✓	✓			✓					
Shankar *et al.* (2013)	✓	✓						✓		✓	✓	✓			✓	✓		
Sazvar *et al.* (2014)							✓	✓				✓		✓			✓	
Kannan *et al.* (2013)		✓								✓				✓				
Govindan *et al.* (2013)	✓		✓				✓	✓						✓		✓		✓
Subulan *et al*. (2014)	✓	✓		✓	✓	✓		✓		✓		✓			✓	✓		
Coskun *et al*. (2015)	✓		✓					✓				✓		✓			✓	
Rodrigues *et al*. (2015)												✓		✓				✓
Amin and Zhang (2013)	✓			✓							✓			✓		✓		
Yang et al. (2009)	✓							✓		✓		✓			✓			
Wu and Chang (2015)									✓					✓	✓	✓		
Soleimani and Kannan (2015)	✓	✓	✓			✓		✓		✓	✓	✓			✓			
Zolfagharinia *et al*. (2014)								✓							✓		✓	
Kusi-Sarpong *et al*. (2014)									✓					✓	✓			
Garg et al. (2015)	✓	✓					✓					✓		✓	✓			✓

Chapter 3

3 An integrated trade-off model for green supply chain planning: Focusing on Carbon Dioxide Emission, Total Costs, and Service

In this chapter, in order to develop a new mathematical model in the context of GSCP, it is taken into account that the integrated supply chain network has five echelons entailing multi-supplier, multi-assembler, multi-DC, multi-retailer, and end customers which collaborate with each other effectively. The proposed model captures the trade-offs between the total costs and service levels. Here, it is assumed that carbon emissions originate from three major sources: (a) The distribution of the components by suppliers to assemblers, where the emissions level is based on the traveled distance and amounts of products transported; (b) The distribution of the products from assemblers to distribution centers and from distribution centers to retailers. For both channels the CO_2 emissions level is computed based on the traveled distance and amounts of the products transported; and (c) The facility (assembly sites, and distribution centers), where the amount of CO_2 emissions is proportional to the area (Agency, I.E., 2014). All considered costs are assumed to be known and accurately determined over the planning horizon. Two main objective functions will be considered: 1) Minimizing the total costs of the supply chain, which also contains carbon emissions costs. 2) Maximizing service levels.

3.1 Assumptions for Modeling

The following assumptions are taken into account:

- Different kinds of components are shipped into assembly plants from some selected suppliers. Then, a variety of products will be provided by assembling different sets of components. The final products will be delivered to a set of distribution centers and consequently will be distributed among different retailers. End customers place their orders to these retailers. Figure 3-1 shows a schematic of this multi-echelon supply chain.
- An Integrated GSCP will be developed over a defined and limited production planning horizon, which contains multiple periods.
- Demand of each product type forecasts for the following T periods based on the history of prior data.
- Each retailer may encounter shortages in meeting customers' demands and partial backordering which is applied when a stock-out occurs related to each type of product.
- Each potential supplier has a definite and limited capacity for providing different components in each period and has the capability of procuring all kinds of components.

- For each supplier candidate, the selling price of the components is definite and known.
- All costs are assumed to be known and accurately determined over the planning horizon.
- Distribution centers can hold inventory, but retailers prefer not to hold any inventory. Additionally, assemblers fabricate final products by using components based on customers' predicted demands and they prefer to hold inventory related to a variety of components.
- The ordering set-up costs of suppliers are fixed and independent, meaning that for different types of ordering products or various amounts of ordering, the ordering cost will be the same.
- There are limitations of capacity for dispatching products from assemblers to distribution centers and sequentially from distribution centers to retailers.

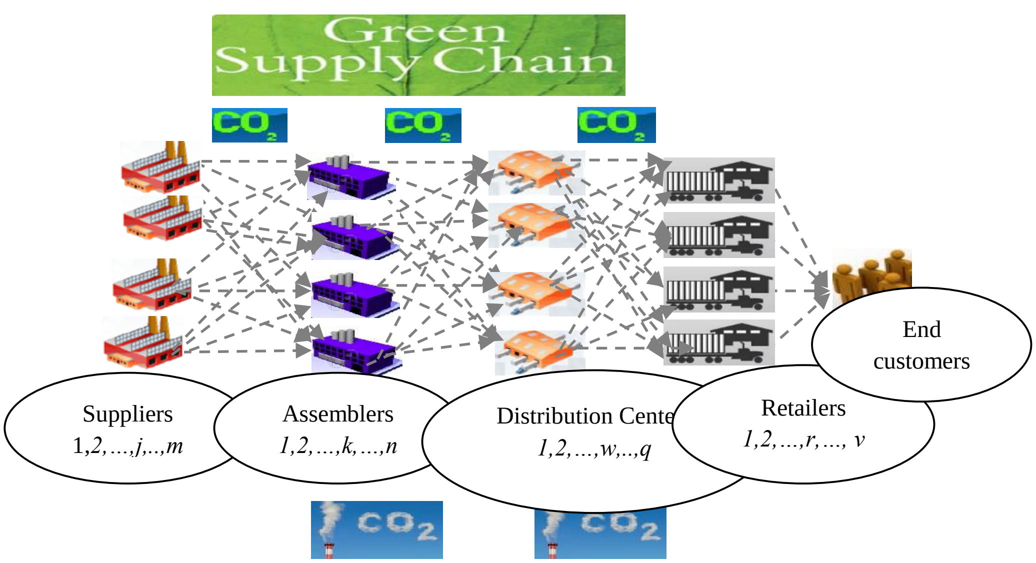

Figure 3-1: The schema of considered multi-echelon supply chain network

3.2 Mathematical Modeling

Considering the abovementioned assumptions and notations mentioned earlier (in the Symbol List), the problem can be modeled as follows. Equations and constraints are explained in the next section.

Objective Functions:

$$Minimizing\ Total\ Costs: Min\ TC = U_1 + U_2 + U_3 + U_4 + U_5$$

Equation 3.2-1

$$Maximizing\ Service\ levels: Max\ SL_{i,r,t} = 1 - \frac{\sum_{l=1}^{t} BR_{i,r,t}}{\sum_{l=1}^{t} D_{i,r,t}} \quad \forall i,r,t$$

Equation 3.2-2

Subject to:

$$U_1 = \theta.\left(CO_2^{Emissions} - CO_2^{Allowed}\right)$$

Equation 3.2-3

$$\begin{aligned} CO_2^{Emissions}: & \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{k'=1}^{n}(\mu_0.E_k.Ar_k) \\ & + \sum_{t=1}^{T}\sum_{w=1}^{q}\sum_{w\prime=1}^{q}(\mu_0.E_w.Ar_w) \\ & + \sum_{t=1}^{T}\sum_{i=1}^{p}\sum_{k=1}^{n}\sum_{w=1}^{q}\sum_{r=1}^{v}\mu_{tr}\,.\left(CC_{k,w}.V_{i,k,w,t} + CC_{w,r}.Q_{i,w,r,t}\right) \\ & + \sum_{t=1}^{T}\sum_{u=1}^{a}\sum_{j=1}^{m}\sum_{k=1}^{n}\left(\mu_{tr}.CC_{j,k}.Z_{u,j,k,t} + \mu_0.Z_{u,j,k,t}\right) \end{aligned}$$

Equation 3.2-4

$$U_2 = \sum_{t=1}^{T}\sum_{j=1}^{m}\sum_{k=1}^{n}\sum_{u=1}^{a}\left(\partial_u . CC_{j,k} . Z_{u,j,k,t}\right) + \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{u=1}^{a}\left(hu_{u,k} . IU_{u,k,t}\right) + \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{j=1}^{m}\left(O_j . Y_{j,k,t}\right) + \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{j=1}^{m}\sum_{u=1}^{a}\left(S_{u,j} . Z_{u,j,k,t}\right)$$

Equation 3.2-5

$$U_3 = \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{w=1}^{q}\sum_{i=1}^{p}\left(\partial_i . CC_{k,w} . V_{i,k,w,t}\right) + \sum_{t=1}^{T}\sum_{k=1}^{n}\sum_{i=1}^{p}\left(\left(\tau_{i,k} . \beta_{i,k,t}\right) + \left(Cpr_{i,k} . X_{i,k,t}\right) + \sum_{u=1}^{a}\left(\rho_{u,i,k} . F_{i,u} . X_{i,k,t}\right)\right)$$

Equation 3.2-6

$$U_4 = \sum_{t=1}^{T}\sum_{w=1}^{q}\sum_{r=1}^{v}\sum_{i=1}^{p}\left(\partial_i . CC_{w,r} . Q_{i,w,r,t}\right) + \sum_{t=1}^{T}\sum_{w=1}^{q}\sum_{i=1}^{p}\left(\left(hw_{i,w} . IW_{i,w,t}\right) + \sum_{k=1}^{n}\left(Trp_{i,k,w} . V_{i,k,w,t}\right)\right)$$

Equation 3.2-7

$$U_5 = \sum_{t=1}^{T}\sum_{r=1}^{v}\sum_{i=1}^{p}\left((\varphi_{i,r} . \alpha_{i,r,t}) + (\pi r_{i,r} . BR_{i,r,t}) + \sum_{w=1}^{q}(Trw_{i,w,r} . Q_{i,w,r,t})\right)$$

Equation 3.2-8

$$IU_{u,k,t} = IU_{u,k,t-1} + \sum_{j=1}^{m} Z_{u,j,k,t} - \sum_{i=1}^{p} \left(F_{i,u}.X_{i,k,t}\right) \qquad \forall u,k,t$$

Equation 3.2-9

$$\sum_{k=1}^{n} Z_{u,j,k,t} \leq CS_{u,j} \qquad \forall u,j,t$$

Equation 3.2-10

$$IU_{u,k,t} \leq MI_{u,k,t} \qquad \forall u,k,t$$

Equation 3.2-11

$$(\sum_{l=t}^{T} \sum_{i=1}^{p} \left(F_{i,u}.X_{i,k,t}\right)).Y_{j,k,t} \leq Z_{u,j,k,t} \qquad \forall u,j,k,t$$

Equation 3.2-12

$$BR_{i,r,t} = BR_{i,r,t-1} + D_{i,r,t} - \left(\sum_{w=1}^{q} Q_{i,w,r,t}\right) \qquad \forall i,r,t$$

Equation 3.2-13

$$IW_{i,w,t} = IW_{i,w,t-1} + \sum_{k=1}^{n} V_{i,k,w,t} - \sum_{r=1}^{v} Q_{i,w,r,t} \qquad \forall i,w,t$$

Equation 3.2-14

$$\sum_{w=1}^{q} V_{i,k,w,t} = X_{i,k,t} \qquad \forall i,k,t$$

Equation 3.2-15

$$Q_{i,w,r,t} \leq \delta_{w,r}.CTrw_{i,w,r} \qquad \forall i,w,r,t$$

Equation 3.2-16

$$V_{i,k,w,t} \leq \gamma_{k,w}.CTrp_{i,k,w} \qquad \forall i,k,w,t$$

Equation 3.2-17

$$IW_{i,w,t} \leq Stw_{i,w} \qquad \forall i,w,t$$

Equation 3.2-18

$$X_{i,k,t} \leq \beta_{i,k,t}.M^{\infty} \qquad \forall i,k,t$$

Equation 3.2-19

$$D_{i,r,t} \leq \alpha_{i,r,t}.M^{\infty} \qquad \forall i,r,t$$

Equation 3.2-20

$$X_{i,k,t} \leq G_{i,k} \qquad \forall i,k,t$$

Equation 3.2-21

$$IU_{u,k,t}, Z_{u,j,k,t}, Q_{i,w,r,t}, V_{i,k,w,t}, X_{i,k,t}, BR_{i,r,t}, IW_{i,w,t} \in Z^{+} \cup \{0\} \qquad \forall i,j,u,k,r,w,t$$

Equation 3.2-22

$$Y_{j,k,t}, \delta_{w,r}, \gamma_{k,w}, \beta_{i,k,t}, \alpha_{i,r,t} \in \{0,1\} \qquad \forall i,k,r,w,t$$

Equation 3.2-23

As a first step to solve the proposed optimization model, the Bounded objective[2] method is applied to convert the bi-objective mixed-integer model to a single objective model. Here, the second objective which refers to maximizing service levels is considered as a constraint. Moreover, we have taken upper bounds and lower bounds for service levels into account as follows:

$$SL_{i,r,t} = 1 - \frac{\sum_{l=1}^{t} BR_{i,r,t}}{\sum_{l=1}^{t} D_{i,r,t}} \qquad \forall i,r,t$$

Equation 3.2-24

$$SL_{i,r,t}^{min} \leq SL_{i,r,t} \leq 1 \qquad \forall i,r,t$$

Equation 3.2-25

[2] Bounded objective method is one of the well-grounded approached of multi-objective optimization which can be used to get more information and sensitivity analysis to the above-mentioned problem. In this method, the main objective function is minimized and all other objective functions are considered in constraints with some satisfactory bounds (Marler and Arora, 2004; Kadry and Hami, 2014)

3.2.1 Expounded on Equations and Constraints

In the above proposed mathematical model in Equation 3.2-1, the main objective function demonstrates the carbon emission costs as well as the total costs of the supply chain. It includes five different terms: U_1, U_2, U_3, U_4, and U_5. Term U_1 is related to carbon emission costs by defining θ (Average expected cost of carbon credits in $/tons of CO_2) as a parameter, which multiplies the difference between the amount of produced CO_2 and the maximum amount of allowed CO_2 emission (Equation 3.2-2). Carbon emissions are calculated across the supply chain by considering the three major sources of producing CO_2 as shown in Equations 3.2-3 and 3.2-4.

Term U_2 refers to a variety of costs of components: a) transportation costs of components from suppliers to assemblers, b) holding costs of inventory at assembly sites, c) fixed ordering costs, and d) purchased costs (Equation 3.2-5). Term U_3 denotes the assembly costs: a) transportation costs of products by assemblers to distribution centers, b) fixed costs of assembling, c) costs of regular time assembling, and d) customization costs of components in assembling customized products (Equation 3.2-6). Term U_4 is related to distribution center costs: a) transportation costs of products carried from assemblers to distribution centers, b) holding costs of inventory at distribution centers, and c) transportation costs of products from distribution centers to retailers, (Equation 3.2-7). Term U_5 is associated with retail costs: a) transportation costs of products carried from distribution centers to retailers, b) set-up costs of products at retail sites per order, and c) backordering costs of products at retail sites (Equation 3.2-8).

As it was described earlier, the second objective function is considered as a constraint and substituted by equation (Equation 3.2-24) and constraint (Equation 3.2-

25). The relationship among service levels at retail sites, demands, and back orderings are shown by equation (Equation 3.2-24). Constraint (Equation 3.2-25) indicates that the value of service levels, which is one of multiple decision variables in the proposed model, can vary between the values of parameter $SL_{i,r,t}^{min}$ and the value of 1. The parameter of $SL_{i,r,t}^{min}$ is the minimum service level at retail sites determined unanimously by retailers in order to meet their customers' demands, and it varies between 0 and 1. Balanced constraints related to components at assembly plants are taken into account in Equation 3.2-9. Constraint 3.2-10 stands for the capacity limitation of suppliers for providing various components. Constraint 3.2-11 demonstrates the storage capacity of assemblers for holding components. Constraint 3.2-12 certifies that there is not an order for procuring components without charging an appropriate transaction cost.

Balanced constraints related to retailers are considered in Equation 3.2-13 and for distribution centers in Equation 3.2-14. Constraint 3.2-15 guarantees that in each period, each assembler ships all the produced final products to a variety of distribution centers and doesn't hold any inventory of final products. Constraint 3.2-16 refers to the capacity limitation of transporting final products from distribution centers to retailers. Similarly, constraint 3.2-17 stands for the capacity limitation of carrying products from assemblers to distribution centers. Constraint 3.2-18 demonstrates the storage capacity for holding products at distribution centers. Constraint 3.2-19 refers to whether assembling of products is set up in assembly plants or not. Correspondingly, constraint 3.2-20 denotes whether retailers place an assembly order for products or not. Constraint 3.2-21 refers to the maximum capacity of assembling at assembly plants. Moreover, continuous values for orders, amounts of inventory related to components at assembly plants, amounts of producing final products, amounts of backordering, and amounts of holding inventory at distribution centers have been satisfied through constraint 3.2-22. Furthermore, constraint 3.2-23 sets the values of binary variables.

3.3 Selected Solution Method for the Proposed Model

The nature of the proposed mathematical model for GSCP is that of (MINLP); therefore, in this study the defined mathematical problem is solved with three different methods. As a first method, the B&B Algorithm is applied to achieve an optimum solution and the model is coded in Lingo software (version: Lingo[3] 14.0). Regarding the second method, the proposed model is coded in MATLAB software (version: R2014b) and the optimization tool of "FminCon" is applied. As a third solution method, a novel metaheuristic algorithm named Grey Wolf Algorithm is applied to achieve the best solution. All of the achieved results are also analyzed and discussed.

3.3.1 Finding a local optimal solution using the Branch and Bound algorithm

In the first step, an optimization solver, the B&Bsolver, is utilized. The nature of the proposed mathematical model for GSCP is that of MINLP; therefore, in this study a

[3] Lingo is categorized as a modeling support system. It is suitable for solving linear and NLP problems, multi-criteria decision making, inventory management problems, queuing problems, etc. (Trzaskalik and Michnik, 2002; Vob and Woodruff, 2005)

local optimum solution is achieved by coding the model in Lingo software (version: Lingo[4] 14.0) and applying the B&B algorithm. In the B&B technique, the model is split into subclasses to be solved with convex (minimization problem) or linear approximations that form a lower bound on the overall cost within the subdivision. With subsequent divisions, at some points an actual solution will be achieved which cost is equal to the best lower bound obtained for any of the approximate solutions. This solution is optimal, though probably not unique. The algorithm may also be stopped early, with the assertion that the best possible solution is within a tolerance from the best point found; such points are called ε-optimal. Terminating to ε-optimal point is usually needed to certify finite termination. This is particularly beneficial for large, difficult problems and problems with uncertain costs or values where the uncertainty can be projected with proper reliability estimations (Bussieck and Vigerske, 2010).

3.3.2 Finding optimal solutions using a gradient-based algorithm

In this step, the proposed model is coded in MATLAB software (version: R2014b) by defining the objective function, linear and nonlinear constraints. Then, the "FminCon" a gradient-based optimization tool, which is one of MATLAB solvers well-fitted to nonlinear constrained minimization problems, is utilized to search for the best solution. After choosing the "FminCon" solver, based on the complexity and state of the mathematical model, the interior point algorithm was selected as it is generally

[4] Lingo is categorized as a modeling support system. It is suitable for solving linear and NLP problems, multi-criteria decision making, inventory management problems, queuing problems, etc. (Trzaskalik and Michnik, 2002; Vob and Woodruff, 2005)

recommended as the most robust algorithm, and most likely to solve difficult problems (Wu *et al.*, 2007a). This solver, which is integrated with an interior point algorithm, works by evaluating the objective function at some set of locations that it supplies. A simple way of understanding this algorithm is that at the beginning of each iteration, it must evaluate the gradient of the objective function at the current point. This gradient evaluation will require *n* objective function evaluations, since it already knows the value of the function at that location from the previous iteration. It might take one, or a couple more function evaluations based on this information to choose a new location to start the next iteration. At the beginning of the next iteration, the algorithm will need to re-compute the gradient. It can be generally assumed that "FminCon" will take *n* function evaluations plus a few more evaluations per each of the iterations. The interior-point approach to a nonlinear constrained minimization problem is to solve a sequence of approximate minimization problems.

The original problem is defined as follows:

$$\underset{x}{Min}\, f(x)$$

Equation 3.3.2-1

Subject to:

$$h(x) = 0 \text{ and } g(x) \leq 0$$

Equation 3.3.2-2

For each $\mu > 0$, the approximate problem is as follows:

$$\underset{x,s}{\text{Min}}\, f_{\mu}(x, s) = \underset{x,s}{\text{Min}}\, f_{\mu}(x) - \mu \sum_{i} \text{Ln}(\, s_i)$$

Equation 3.3.2-3

Subject to:

$h(x) = 0$ and $g(x)$+s=0

Equation 3.3.2-4

There are as many slack variables s_i as there are various inequality constraints g. The s_i variables are restricted to be positive to keep $Ln\ (s_i)$ bounded. As μ decreases to zero, the minimum of f_μ should approach the minimum of the function f. The added logarithmic term is named a barrier function. The approximate problem (Equations 3.3.2-3 and 3.3.2-4) is a sequence of equality constrained problems. These are simpler to solve than the original inequality-constrained problem (Equations 3.3.2-1 and 3.3.2-2). To solve the approximate problem, the interior-point algorithm utilizes one of two main types of steps at each iteration: a direct step in (x, s) (Newton step) or a conjugate gradient step. They are described in the following subsections.

3.3.2.1 A direct step in (x, s) or a Newton step

This step attempts to solve the KKT equations for the approximate problem through a linear approximation. The KKT conditions are analogous to the condition that the gradient must be zero at a minimum, adapted to take constraints into consideration. Under differentiability and constraint qualifications, the KKT conditions offer the necessary conditions for a solution to be optimal. Under convexity, these conditions are also sufficient. The difference is that the KKT conditions hold for constrained problems. The KKT conditions employ the auxiliary Lagrangian function:

$$L(x,\lambda) = f(x) + \sum \lambda_{g,i} \cdot \underset{i}{\mathrm{g}}(x) + \sum \lambda_{h,i} \cdot \underset{i}{h}(x)$$

Equation 3.3.2.1-1

The vector of λ (which is the concatenation of λ_g and λ_h) is the Lagrange multiplier vector. Its length is the total number of constraints. The KKT conditions are as follows:

$$\nabla_x L(x,\lambda) = 0$$

Equation 3.3.2.1-2

$$\lambda_{g,i} . \underset{i}{\mathrm{g}}(x) = 0 \,, \forall i$$

Equation 3.3.2.1-3

$$\begin{cases} g(x) \leq 0 \\ h(x) = 0 \\ \lambda_{g,i} \geq 0 \end{cases}$$

Equation 3.3.2.1-4

In defining the direct step, the following variables and definitions are applied:

H: It denotes the Hessian[5] of the Lagrangian of f_μ and is computed by Equation 3.3.2.1-5.

$$H = \nabla^2 f(x) + \sum_i \lambda_i \nabla^2 \underset{i}{\mathrm{g}}(x) + \sum_j \lambda_j \nabla^2 \underset{j}{h}(x)$$

Equation 3.3.2.1-5

[5] Hessian is a square matrix of second-order partial derivatives of a function and it explains the local curvature of a function of many variables.

J_g : It represents the Jacobian of the constraint function *g*.

J_h : It stands for the Jacobian of the constraint function *h*.

λ: It refers to the Lagrange multiplier vector associated with constraints *g*.

y: It expresses the Lagrange multiplier vector associated with *h*.

e: It signifies the vector of ones the same size as *g*.

The following equation outlines the direct step ($\Delta\, x$, $\Delta\, s$), here S= diagonal (s) and Λ =diag(λ):

$$\begin{bmatrix} H & 0 & J_h^T & J_g^T \\ 0 & S\Lambda & 0 & -S \\ J_h & 0 & I & 0 \\ J_g & -S & 0 & I \end{bmatrix} \begin{bmatrix} \Delta\, x \\ \Delta\, s \\ -\Delta\, y \\ -\Delta\, \lambda \end{bmatrix} = \begin{bmatrix} \nabla f - J_h^T y - J_g^T \lambda \\ S\lambda - \mu e \\ h \\ g + s \end{bmatrix}$$

Equation 3.3.2.1-6

This equation comes directly from making an effort to solve Equations 3.3.2.1-2 and 3.3.2.1-3 employing a linearized Lagrangian. To solve this equation for ($\Delta\, x, \Delta\, s$), the algorithm makes an LDL-factorization (where L is a lower unit triangular matrix and D is a diagonal matrix) of the matrix. The LDL-factorization is an effective method of solving Ax = b for a large symmetric positive definite matrix A. The LDL-factorization needs half the computation of Gaussian elimination (LU decomposition), and is always stable. It is more effective than Cholesky factorization[6] because it keeps away from computing the square roots of the diagonal elements. Assume that matrix A ($A = LDL^T$) has already been ordered by some fill-reducing symmetric permutation (e.g., minimum-degree ordering or nested-dissection ordering). By

[6] Cholesky factorization is a decomposition of a Hermitian, positive-definite matrix into the product of a lower triangular matrix and its conjugate transpose.

default, LDL references only the diagonal and lower triangle of A, and assumes that the upper triangle is the complex conjugate transpose of the lower triangle. A well-known algorithm that performs LDL-factorization is presented by Wu, *et al*. (2007a).

3.3.2.2 A conjugate gradient step

As a default, the interior point algorithm first makes an effort to take a direct step. If it cannot, it attempts a conjugate gradient step. One case where it does not take a direct step is when the approximate problem is not locally convex close to the current iteration. At each iteration the algorithm decreases a merit function, such as Equation 3.3.2.2-1 (Waltz *et al*. 2006).

$$\underset{\mu}{f}(x,s)+\vartheta\|(h(x),g(x)+s\|$$

Equation 3.3.2.2-1

The parameter ϑ may increase with iteration number so as to force the solution towards feasibility. If an attempted step does not decrease the merit function, the algorithm rejects the attempted step, and tries a new step. If either the objective function or a nonlinear constraint function returns a complex value or an error at iteration x_j, the algorithm rejects x_j. The rejection has the same influence as if the merit function did not decrease adequately: the algorithm then tries a different, shorter step. In this approach, in order to solve the approximate problem determined by Equations 3.3.2-3 and 3.3.2-4, the algorithm adapts both *x* and *s*, keeping the slacks *s* positive. The tactic is to minimize a quadratic approximation to the approximate problem in a trust region, bound by the linearized constraints. The region that the approximate model is trusted is named the trust region. A trust region is typically a neighborhood centered at the current iterate. The trust region is adjusted from iteration to iteration. Roughly speaking, if the computations indicate the approximate model fit the original problem well, the trust region can be enlarged. Particularly, let *R* represent the radius of the trust region, and let other variables be defined as in Direct Step. The algorithm achieves Lagrange multipliers by approximately solving the *KKT* equations in the least-squares sense, subject to λ being positive as demonstrated by the following equation:

$$\nabla_x L = \nabla_x f(x) + \sum_i \lambda_i \nabla \underset{i}{g}(x) + \sum_j y_j \nabla \underset{j}{h}(x) = 0$$

Equation 3.3.2.2-2

Then it takes a step ($\Delta\, x$, $\Delta\, s$) to approximately solve the following model:

$$\min_{\Delta\, x, \Delta\, s} \nabla\, f^T \Delta\, x\ + \frac{1}{2} \Delta x^T \nabla_{xx}^2 L\, \Delta x + \mu\, e^T S^{-1} \Delta\, s + \frac{1}{2}\, \Delta s^T\, S^{-1} \Lambda \Delta s$$

Equation 3.3.2.2-3

Subject to the linearized constraints:

$$g(x) + J_g \Delta x + \Delta s = 0,\ \ h(x) + J_h \Delta x = 0$$

Equation 3.3.2.2-4

To solve the Equation 3.3.2.1-4, the algorithm attempts to minimize a norm of the linearized constraints inside a region with radius scaled by *R*. Then Equation 3.3.2.1-3 is solved with the constraints being to match the residual from solving Equation 3.3.2.1-4, staying within the trust region of radius *R*, and keeping *s* strictly positive.

3.3.2.3 Tolerances and Stopping Criteria

The sum of iterations in an optimization depends on a solver (algorithm)'s stopping criteria. These criteria contain several tolerances that can be set. Usually, a tolerance is a threshold which, if crossed, stops the iterations of a solver. Here, as we have coded our defined mathematical model in MATLAB software and applied the "FminCon" solver integrated with interior point algorithm as a solution method, the following tolerances and stopping criteria are considered.

- X tolerance: It's a lower bound on the size of a step, meaning the norm of $(x_i - x_{i+1})$. If the algorithm attempts to take a step that is smaller than *X* tolerance, the iterations end. *X* tolerance can also be used as a relative bound, meaning iterations end when:

$$|(x_i - x_{i+1})| < (X\ tolerance * (1 + |x_i|))$$

Equation 3.3.2.3-1

- Function tolerance: It's a lower bound on the change in the value of the objective function during a step. If $|(\mathrm{f}(\mathrm{x_i}) - \mathrm{f}(\mathrm{x_{i+1}})| < Function\ tolerance$, the iterations end. Function tolerance can also be applied as a relative bound, meaning iterations end when:

$$|(f(x_i) - f(x_{i+1})| < (Function\ tolerance * (1 + |f(x_i)|))$$

Equation 3.3.2.3-2

- Function tolerance is most often a bound on the first-order optimality measure. First-order optimality is a measure of how close a point x is to optimal.
- Nonlinear tolerance constraint: It's an upper bound on the magnitude of any constraint functions. If it is not satisfied (i.e., if the magnitude of the constraint function exceeds nonlinear tolerance constraint), the algorithm attempts to continue, unless it is stopped for another reason.
- Max iterations: It's a bound on the number of solver iterations.
- Max function evaluations: It's a bound on the number of function evaluations.
- Minimum/Maximum perturbation: It's a bound on the number of perturbation for finite differencing of derivatives.

3.3.3 Finding optimal solutions using Grey Wolf Optimizer algorithm

Based on the literature, meta-heuristic methods can be categorized into two main classes: single-solution-based (such as Simulated Annealing method) and population-based. In the single-solution-based metaheuristics the search process starts with one candidate solution. This single candidate solution is then improved over the course of iterations. Population-based meta-heuristics, however, perform the optimization utilizing a set of solutions (population). In this case the search process starts with a random initial population (multiple solutions), and this population is enhanced over the course of iterations. Population-based meta-heuristics have some advantages compared to single solution-based algorithms: a) multiple candidate solutions share information about the search space which results in sudden jumps toward the promising part of search-space; b) multiple candidate solutions assist each other to avoid locally optimal solutions; c) population-based meta-heuristics generally have greater exploration compared to single solution-based algorithms.

One of the interesting branches of the population-based metaheuristics is swarm intelligence. The Grey Wolf Optimizer algorithm is a new swarm intelligence-based method which mimics the leadership hierarchy and the hunting mechanism of grey wolves in nature. This algorithm proposed by Mirjalili *et al.* (2014).

Grey wolves mostly prefer to live in a pack. The leaders are a male and a female, called alphas. The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. The beta wolf can be either male or female, and he/she is probably the best candidate to be the alpha in case one of the alpha wolves passes away or becomes very old. The third level in the hierarchy of grey wolves is Delta wolves. Delta wolves have to submit to alphas and betas. Besides the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. The lowest ranking grey wolf is omega. The omega plays the role of scapegoat. Omega wolves always have to submit to all the other dominant wolves (Figure 3-2).

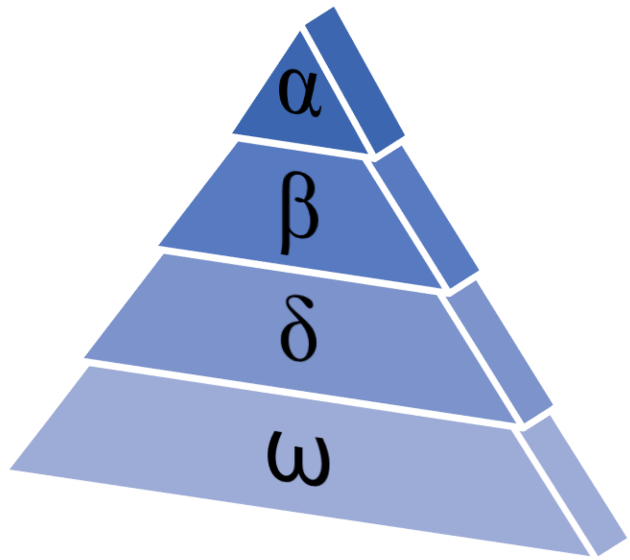

Figure 3-2: Hierarchy of grey wolf (dominance decreases from top down) (Mirjalili *et al.*, 2014)

The main phases of grey wolf hunting are as follows:

- Searching the prey
- Encircling and harassing the prey until it stops moving.
- Attacking towards the prey
- Hunting the prey

Figure 3-3: Hunting behavior of grey wolves [7](Mirjalili *et al.*, 2014)

3.3.3.1 Search for prey

Grey wolves mostly search according to the position of the alpha, beta, and delta. They diverge from each other to search for prey and converge to attack prey. In order to mathematically model divergence, we utilize $\vec{A}$ (a coefficient vector) with random values greater than 1 or less than -1 to oblige the search agent to diverge from the prey. This emphasizes exploration and allows the Grey Wolf Optimizer algorithm to search globally. Figure 3-4 shows that $|A| > 1$ forces the grey wolves to diverge from the prey

[7] Section A is related to chasing, approaching, and tracking prey; sections B, C, and D refer to pursuing, harassing, and encircling; and section E shows the stationary situation and the attack.

to hopefully find a fitter prey. Another element of Grey Wolf Optimizer that favors exploration is $\vec{C}$ (a coefficient vector). The $\vec{C}$ vector can be considered as the effect of obstacles to approaching prey in nature. Normally, there are obstacles in the hunting paths of wolves and in fact prevent them from quickly and conveniently approaching prey. This is exactly what the vector $\vec{C}$ does. Depending on the position of a wolf, it can randomly give the prey a weight and make it harder and farther to reach for wolves, or vice versa.

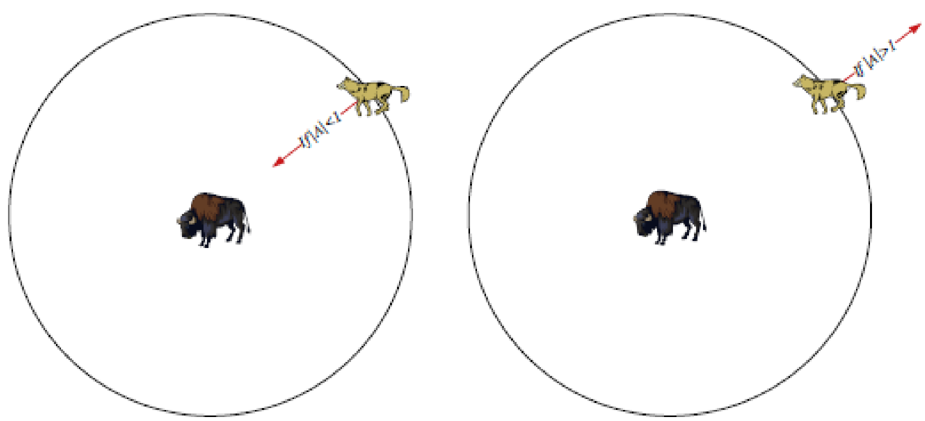

Figure 3-4: Attacking prey versus searching for prey

The $\vec{C}$ vector contains random values in [0, 2]. This component provides random weights for prey in order to stochastically emphasize ($C > 1$) or deemphasize ($C < 1$) the effect of prey in defining the distance. This assists Grey wolf optimizer algorithm to show a more random behavior throughout optimization, favoring exploration and local optima avoidance. It is worth mentioning here that C is not linearly decreased in contrast to A. We deliberately require C to provide random values at all times in order to emphasize exploration not only during initial iterations but also final iterations. This component is very helpful in case of local optimal stagnation, especially in the final iterations.

To sum up, the search process starts with creating a random population of grey wolves (candidate solutions) in the Grey Wolf Optimizer algorithm. Over the course of iterations, alpha, beta, and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance from the prey (Fig. 3-5). The parameter a is decreased from 2 to 0 in order to emphasize exploration and exploitation, respectively. Candidate solutions tend to diverge from the prey when $|A| > 1$ and converge towards the prey when $|A| < 1$. Finally, the GWO algorithm is terminated by the satisfaction of an end criterion.

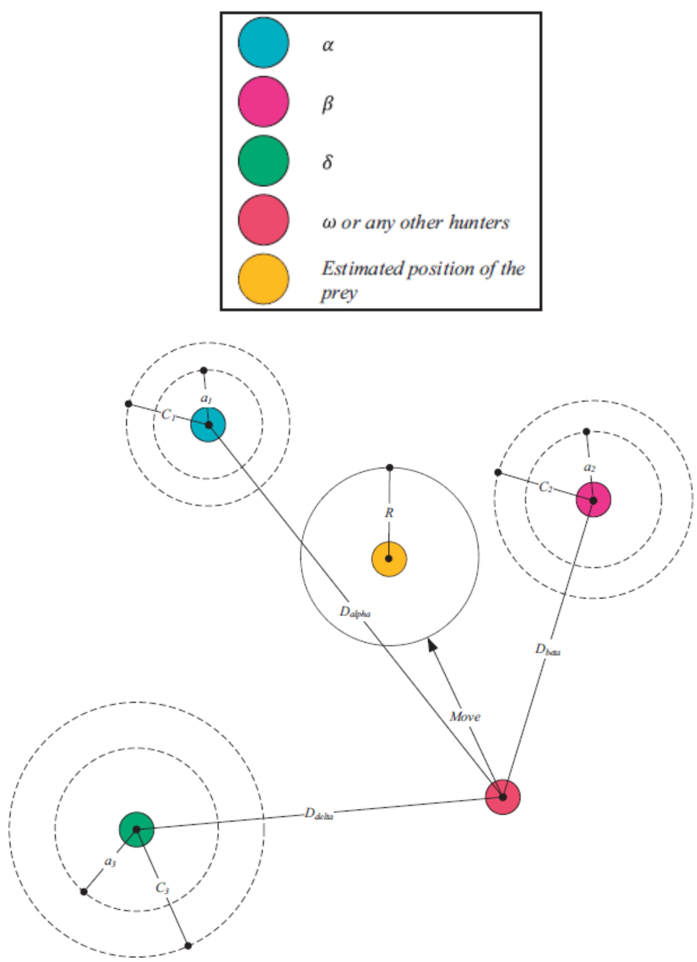

Figure 3-5: Position updating in Grey Wolf optimizer algorithm (Mirjalili *et.al*, 2014)

3.3.3.2 Encircling prey

Grey wolves encircle prey during the hunt. In order to mathematically model encircling behavior the following equations are proposed by Mirjalili *et al.* (2014):

$$\vec{D} = |\vec{C} \,.\overrightarrow{X_p}(t) - \vec{X}(t)|$$

Equation 3.3.3.2-1

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}\,.\, \vec{D}$$

Equation 3.3.3.2-2

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf. The vectors $\vec{A}$ and $\vec{C}$ are computed as follows:

$$\vec{A} = 2\vec{a}\,.\overrightarrow{r_1} - \vec{a}$$

Equation 3.3.3.2-3

$$\vec{C} = 2.\overrightarrow{r_2}$$

Equation 3.3.3.2-4

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0, 1]. Figure 3-6 and Figure 3-7 show how a grey wolf in the position of (X, Y) can update its position according to the position of the prey (X^*, Y^*). A grey wolf can update its position inside the space around the prey in any random location by using Equations Equation 3.3.3.2-1 and 3.3.3.2-2. The same concept can be extended to a search space with *n* dimensions, and the grey wolves will move in hyper-cubes (or hyper-spheres) around the best solution obtained so far.

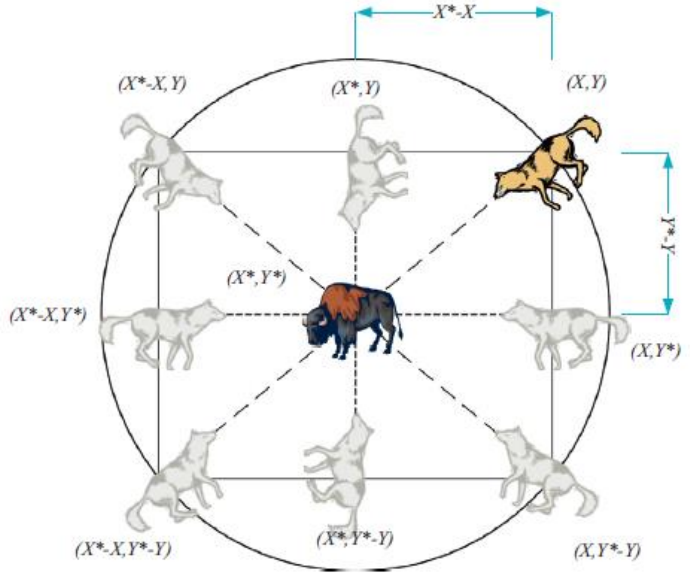

Figure 3-6: 2D position vectors and their possible next locations (Mirjalili *et al.*, 2014)

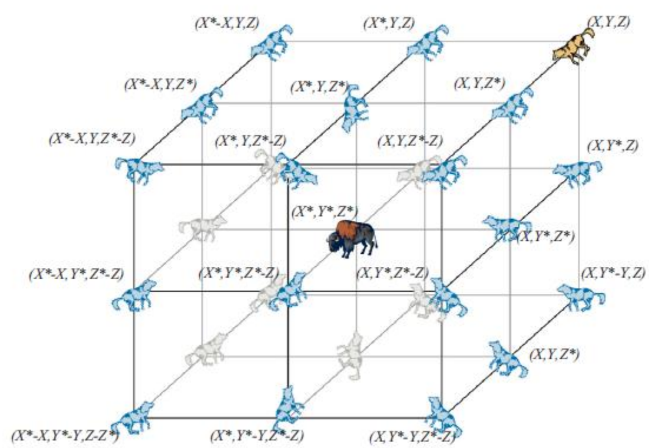

Figure 3-7: 3D position vectors and their possible next locations (Mirjalili *et al.*, 2014)

3.3.3.3 Hunting the prey

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behavior of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are proposed in this regard.

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}\,.\overrightarrow{X_\alpha}(t) - \vec{X}(t)|$$

Equation 3.3.3.3-1

$$\overrightarrow{D_\beta} = |\overrightarrow{C_2}\,.\overrightarrow{X_\beta}(t) - \vec{X}(t)|$$

Equation 3.3.3.3-2

$$\overrightarrow{D_\delta} = |\overrightarrow{C_3}\,.\overrightarrow{X_\delta}(t) - \vec{X}(t)|$$

Equation 3.3.3.3-3

$$\overrightarrow{X_1}(t+1) = \overrightarrow{X_\alpha}(t) - \overrightarrow{A_1}\,.\,\overrightarrow{D_\alpha}$$

Equation 3.3.3.3-4

$$\overrightarrow{X_2}(t+1) = \overrightarrow{X_\beta}(t) - \overrightarrow{A_2}\,.\,\overrightarrow{D_\beta}$$

Equation 3.3.3.3-5

$$\overrightarrow{X_3}(t+1) = \overrightarrow{X_\delta}(t) - \overrightarrow{A_3} \,.\, \overrightarrow{D_\delta}$$

Equation 3.3.3.3-6

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1}(t+1) + \overrightarrow{X_2}(t+1) + \overrightarrow{X_3}(t+1)}{3}$$

Equation 3.3.3.3-7

Figure 3-6 demonstrates how a search agent updates its position according to alpha, beta, and delta in a 2D search space. It can be observed that the final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words, alpha, beta, and delta estimate the position of the prey, and other wolves updates their positions randomly around the prey.

3.3.3.4 Attacking prey

Grey wolves finish the hunt by attacking the prey when it stops moving. In order to mathematically model approaching the prey we decrease the value of $\vec{a}$. Note that the fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. In other words, of $\vec{A}$ is a random value in the interval $[-2a, 2a]$ where a is decreased from 2 to 0 over the course of iterations. When random values of $\vec{A}$ are in $[-1,1]$, the next position of a search agent can be in any position between its current position and the position of the prey. Based on Figure 3-4, $|A| < 1$ forces the wolves to attack towards the prey.

To sum up, the following flowchart shows how the Grey Wolf Optimizer algorithm works.

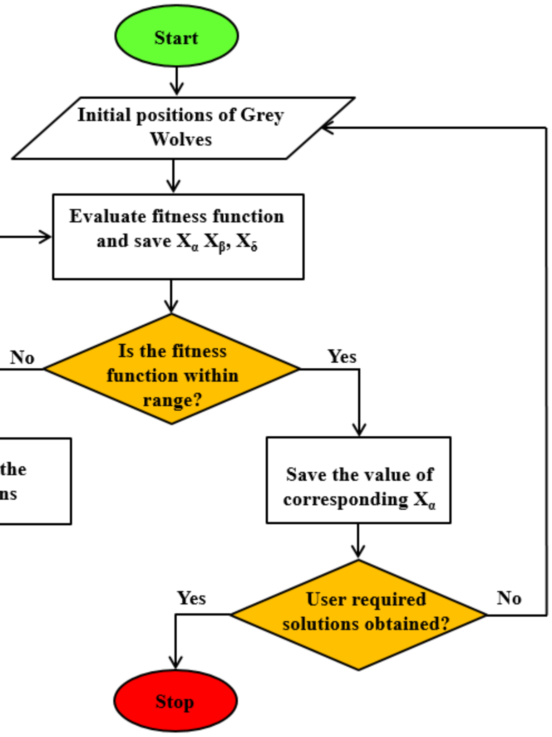

Figure 3-8: The flowchart of Grey Wolf Optimizer algorithm

Pseudo code of the Grey Wolf Optimizer algorithm is also as follows:

Initialize the Grey Wolf Population X_i $(i = 1,2, \dots, n)$

Initialize a, A, and C

Calculate the fitness of each search agent

$\overrightarrow{X_\alpha}$ = *the position of best search agent (alpha wolf)*

$\overrightarrow{X_\beta}$ = *the position of second best search agent (beta wolf)*

$\overrightarrow{X_\delta}$ = *the position of third best search agent (delta wolf)*

While (t< Max number of iterations)

for each search agent

Update the position of the current search agent

End for

Update a, A, and C

Calculate the fitness of all search agents

Update $\overrightarrow{X_\alpha}, \overrightarrow{X_\beta}, \overrightarrow{X_\delta}$

$t = t + 1$

End while

Return $\overrightarrow{X_\alpha}$

In the next section, in order to illustrate the efficiency of the proposed model and solution, a numerical analysis based on a case study is applied to a considered expanded data set. We have utilized the aforementioned methods to achieve the optimal solution.

3.4 Application: Case Study, Computational results, Result analysis

In this step, an expanded production dataset from a supply chain network related to the production of vacuums, scrubbers, carpet extractors, and floor machines located in the Midwestern USA is applied. This network is an integrated structure consisting of three suppliers, three assemblers, three distribution centers, three retailers, and end customers.

As a part of conducting research, related to one of the assemblers, which is located in Ohio, USA, a solid waste assessment study performed. Figure 3-9 demonstrates the Fire and tornado safety plan related to that assembling site. Collecting this data set and performing related analysis were done by team members of BWRAP, Sustainability Laboratory of MIME Department at University of Toledo.

The objective of this recycling research as a part of conducting research were to determine recycling opportunities and to reduce the amount of waste generated at the facility. Table 3.4.2 and Figure 3-10 displays the weight of major solid wastes disposed of periodically by this assembler that originates in the offices and shop are. As shown in Table 3.4.2, the facility currently disposes of approximately 11.92 tons of solid waste periodically. Of that total it was determined that 11.37 tons are recyclable. Currently 8.86 tons out of 11.37 tons are being recycled and 3.07 tons are not recycled. Table 3.4.3 and Figure 3-11 display the major waste streams generated periodically in the offices and shop area of the facility in terms of volume (cubic yards). Results indicate that the studied assembling site currently has an effective and efficient waste management and recycling program in offices and shop area.

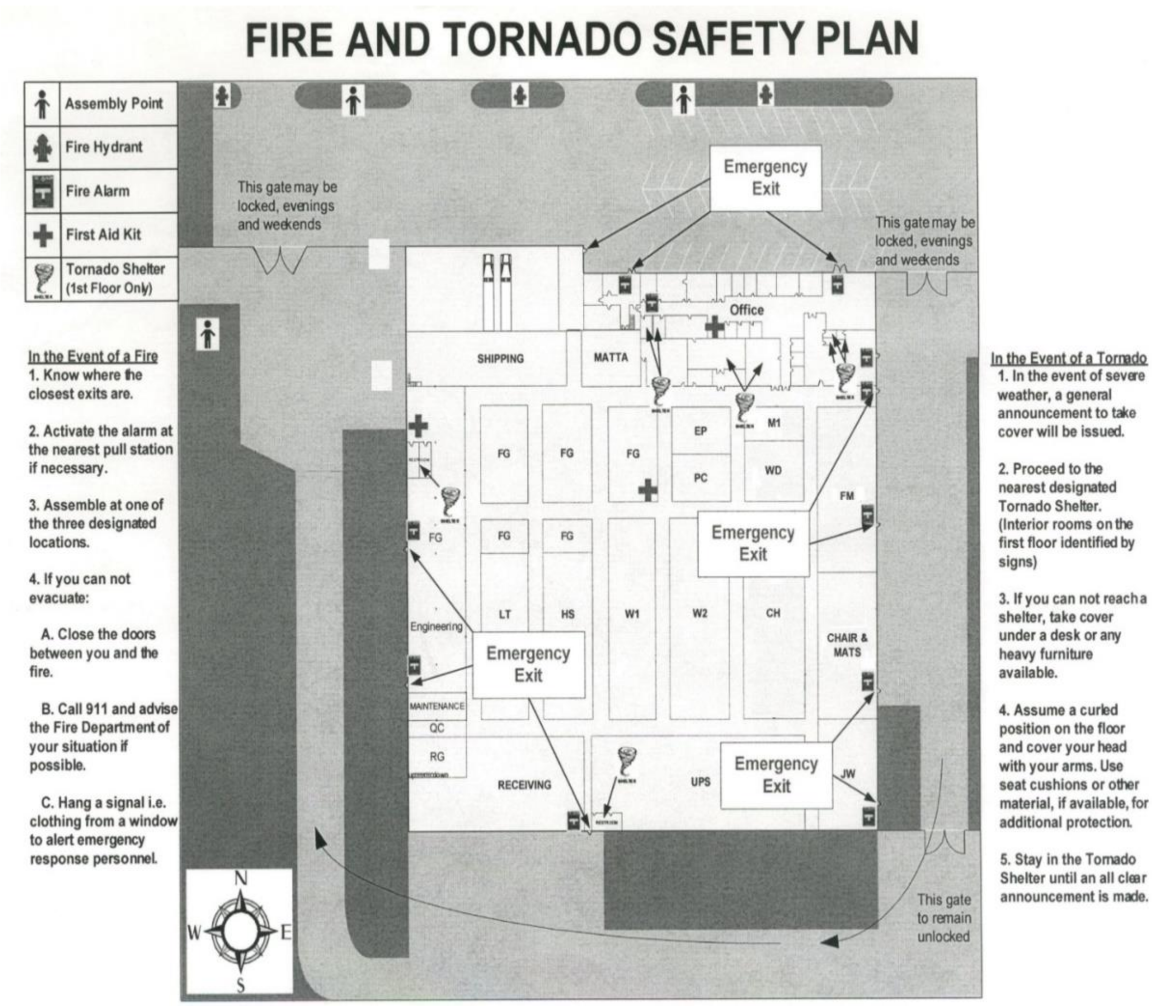

Figure 3-9: Fire and tornado safety plan of an assembler in the considered supply chain network

Table 3.4.1: Periodic tons of recycled and not recycled major solid waste streams

Component	Total Weight (Tons / Period)	% of Total Weight	Waste Recycled (Tons / Period)	Waste Not Recycled (Tons / Period)
Waste Streams That Can Be Recycled				
Mixed Scrap Paper (Such as Packaging Papers)	2.31	19.4%	0.31	2.00
Newspaper	0.00	0.0%	0.00	0.00
Magazines	0.00	0.0%	0.00	0.00
Cardboard	0.61	5.1%	0.56	0.05
Aluminum	0.30	2.5%	0.26	0.04
PET (1)	0.50	4.2%	0.38	0.12
HDPE (2)	6.57	55.1%	6.57	0.00
Other Plastics (such as plastic bandings)	0.10	0.9%	0.00	0.10
Plastic Wrap (Bubble wrap, foam wrap)	0.20	1.7%	0.00	0.20
Other (Scrapping metals, metal bonding, metallic scrap parts)	0.78	6.5%	0.78	0.00
Sub Total	11.37	95.4%	8.86	2.52
Waste Streams That Can Not Be Recycled				
Non-recycling Major Solid Waste (MSW), food waste, wax coated papers, and Styrofoam	0.55	4.6%	0.00	0.55
Sub Total	0.55	4.6%	0.00	0.55
Grand Total	11.92	100%	8.86	3.07

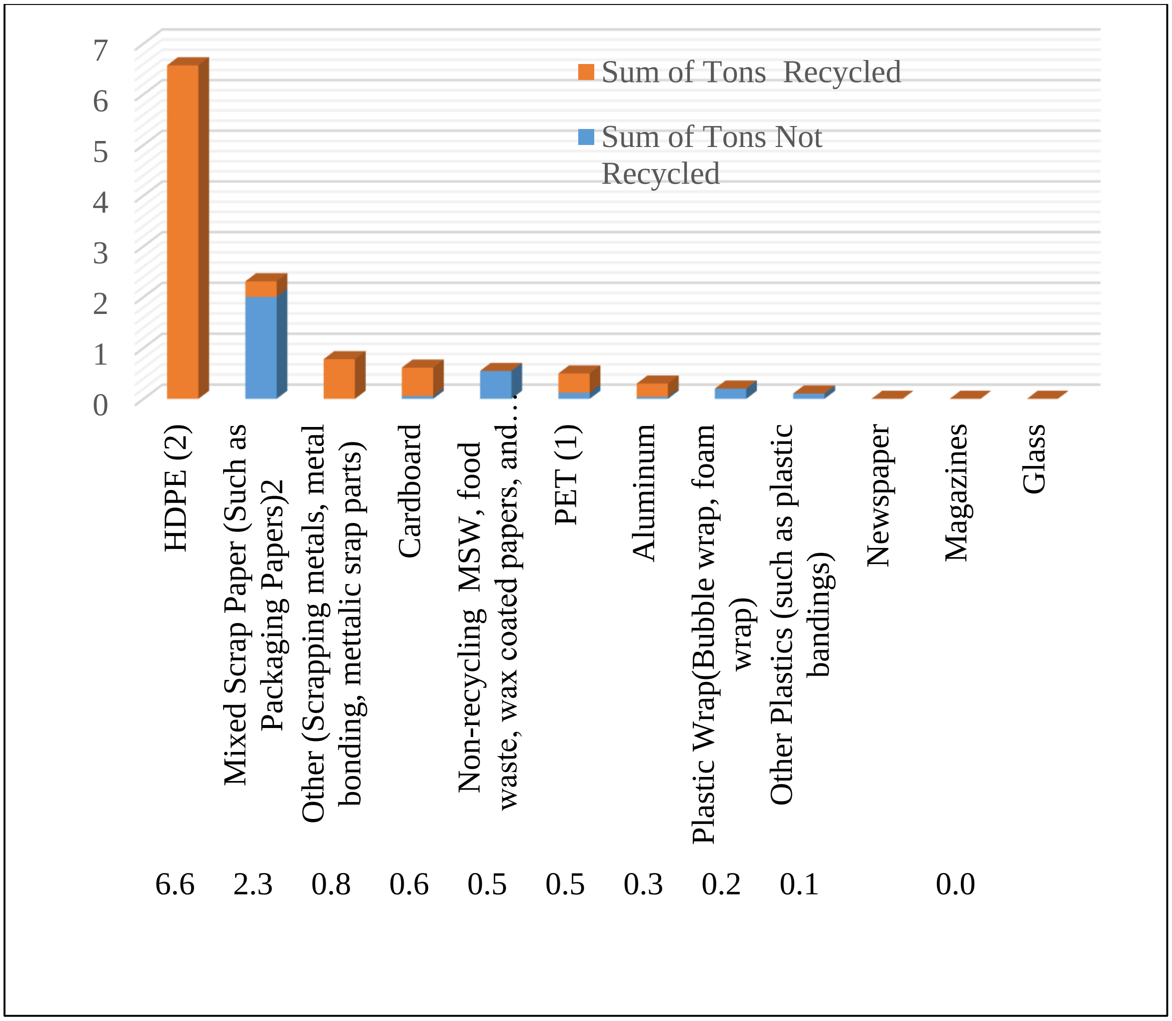

Figure 3-10: Periodic weight of major solid waste stream

Table 3.4.2: Periodic volume of recycled and not recycled major solid waste streams

Component	Total Volume (Yd^3 / Period)	% of Total Volume	Waste Recycled (Yd^3 / Period)	Waste Not Recycled (Yd^3 / Period)
Waste Streams That Can Be Recycled				
Mixed Scrap Paper	41.97	23.3%	5.59	36.38
Newspaper	0.00	0.0%	0.00	0.00
Magazines	0.00	0.0%	0.00	0.00
Cardboard	24.51	13.6%	22.34	2.17
Aluminum	18.74	10.4%	16.41	2.33
PET (1)	24.92	13.8%	18.87	6.05
HDPE (2)	8.21	4.6%	8.21	0.00
Other Plastics (such as plastic bandings)	4.17	2.3%	0.00	4.17
Plastic Wrap (Bubble wrap, foam wrap)	7.60	4.2%	0.00	7.60
Other (Scrapping metals, metal bonding, metallic scrap parts)	29.40	16.3%	29.40	0.00
Sub Total	159.52	88.52%	100.82	58.71
Waste Streams That Can Not Be Recycled				
Non-recycling MSW, food waste, wax coated papers, and Styrofoam	20.69	11.48%	0.00	20.69
Sub Total	20.69	11.48%	0.00	20.69
Grand Total	180.22	100%	100.82	79.40

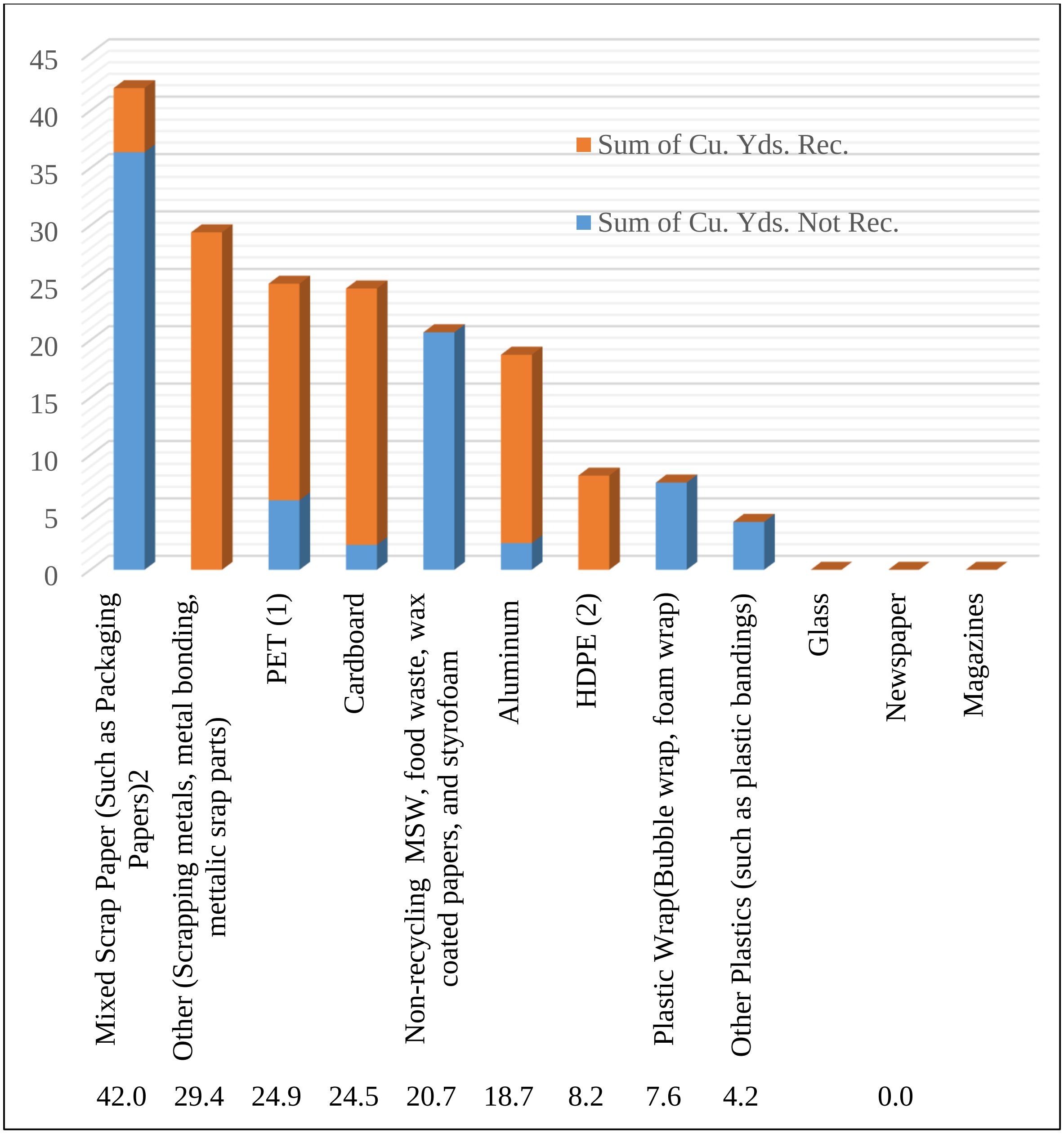

Figure 3-11: Periodic volume of major solid waste stream

It is assumed that the supply chain planning will be determined for three periods. During these three periods, the total cost of both the supply chain and CO_2 emissions will be minimized. This numerical example, has been formulated based on the proposed mathematical model. The values of parameters used as inputs for modeling are shown in Tables 3.4.3 to 3.4.12 as follows.

Table 3.4.3: Demand, Set-up cost ($), and Unit backorder cost ($) of products at retailer's sites

Demand		Period 1	Period 2	Period 3	Set-up cost / Unit backorder cost
Retailer 1	Product 1	770	500	550	15; 30
	Product 2	740	510	520	22; 40
	Product 3	690	500	510	15; 60
Retailer 2	Product 1	700	510	510	20; 60
	Product 2	590	510	500	18; 50
	Product 3	560	500	510	24; 50
Retailer 3	Product 1	760	500	500	18; 45
	Product 2	710	500	520	20; 60
	Product 3	570	510	500	18; 70

Table 3.4.4: Capacity, Unit selling price ($) of components, and Set-up cost ($) per order offered by suppliers

Capacity/Unit selling price	Component 1	Component 2	Component 3	Set-up cost per order
Supplier 1	1,000; 10	1,500; 30	4,000; 18	100
Supplier 2	2,000; 15	3,000; 35	2,000; 20	200
Supplier 3	3,000; 20	3,500; 25	3,000; 15	150

Table 3.4.5: Coefficient of consumption related to components in forming products and Fixed cost of transportation ($) related to products and components per unit distance ($/mile)

Coefficient	Component 1	Component 2	Component 3
Product 1	1	2	2
Product 2	2	1	3
Product 3	2	3	2
The fixed cost of transportation	Product 1/ Component 1	Product 2/ Component 2	Product 3/ Component 3
	0.09; 0.06	0.1; 0.08	0.2; 0.09

Table 3.4.6: Unit customization costs ($) of assembling, Fixed costs of assembling ($), and Unit regular time assembling cost

Customization cost of assembling		Component 1	Component 2	Component 3	Fixed costs of assembling/ Unit regular time assembling cost
Assembler 1	Product 1	20	18	30	30; 12
	Product 2	30	20	14	20; 16
	Product 3	20	20	20	60; 13
Assembler 2	Product 1	25	15	12	50; 13
	Product 2	15	13	15	30; 15
	Product 3	10	18	30	50; 12
Assembler 3	Product 1	10	16	15	40; 10
	Product 2	15	14	11	40; 11
	Product 3	18	16	16	70; 10

Table 3.4.7: Unit inventory holding cost ($) of components and products at assembly and distribution centers per unit time

Inventory holding cost	Assembler 1	Assembler 2	Assembler 3
Component 1	1	1.5	2
Component 2	2	2	2.5
Component 3	1	1	2
Inventory holding cost	DC 1	DC 2	DC 3
Product 1	1	1.5	2
Product 2	2	1	2
Product 3	1	1.5	2

Table 3.4.8: Maximum holding capacity of components at assembly sites by period, Energy requirement (kWh per ft^2) and Size of the facility (ft^2) for assemblers and distribution centers

Maximum holding capacity		Period 1	Period 2	Period 3
Assembler 1	Component 1	300	200	100
	Component 2	115	150	160
	Component 3	150	145	140
Assembler 2	Component 1	120	130	140
	Component 2	110	125	135
	Component 3	130	145	160
Assembler 3	Component 1	160	150	110
	Component 2	140	135	160
	Component 3	115	120	135
		Assembler 1/ DC 1	Assembler 2/ DC 2	Assembler 3/ DC 3
Energy requirement		7.1; 5.5	7.8; 6.5	8.0; 7.0
Area		10,000; 3,000	20,000; 7,000	30,000; 8,000

Table 3.4.9: Maximum capacity of assembling at each assembly site and Store capacity of products at distribution centers in each period

Capacity	Assembler 1/ DC 1	Assembler 2/ DC 2	Assembler 3/ DC 3
Product 1	200; 200	230; 210	210; 220
Product 2	215; 250	220; 260	230; 270
Product 3	240; 265	245; 280	230; 250

Table 3.4.10: Distance, in miles, between various echelons of considered supply chain

Distance	Assembler 1	Assembler 2	Assembler 3
Supplier 1	40	35	25
Supplier 2	50	60	40
Supplier 3	45	45	30
Distance	DC 1	DC 2	DC 3
Assembler 1	30	35	40
Assembler 2	40	100	50
Assembler 3	60	50	55
Distance	Retailer 1	Retailer 2	Retailer 3
DC 1	60	55	40
DC 2	50	65	350
DC 3	60	70	45

Table 3.4.11: Capacity limit to ship products from assemblers to distribution centers and from distribution centers to retailers

Capacity limits to ship products		DC 1	DC 2	DC 3
Assembler 1	Product 1	1,100	1,200	1,300
	Product 2	1,100	1,200	1,100
	Product 3	1,100	1,200	1,000
Assembler 2	Product 1	1,150	1,180	1,200
	Product 2	1,200	1,180	1,100
	Product 3	1,100	1,150	1,170
Assembler 3	Product 1	1,150	1,200	1,150
	Product 2	1,150	1,170	1,180
	Product 3	1,100	1,150	1,160
Capacity limits to ship products		Retailer 1	Retailer 2	Retailer 3
DC 1	Product 1	1,100	1,300	1,250
	Product 2	1,430	1,410	1,300
	Product 3	1,370	1,380	1,400
DC 2	Product 1	1,260	1,270	1,300
	Product 2	1,320	1,360	1,200
	Product 3	1,320	1,350	1,410
DC 3	Product 1	1,400	1,450	1,420
	Product 2	1,220	1,340	1,350
	Product 3	1,420	1,450	1,440

Table 3.4.12: Unit transportation costs ($) of carrying products from assemblers to distribution centers and from distribution centers to retailers

Transportation cost		DC 1	DC 2	DC 3
Assembler 1	Product 1	12	15	18
	Product 2	18	14	16
	Product 3	15	16	18
Assembler 2	Product 1	16	14	15
	Product 2	14	16	18
	Product 3	12	16	19
Assembler 3	Product 1	12	15	18
	Product 2	18	16	14
	Product 3	12	15	14
Transportation cost		Retailer 1	Retailer 2	Retailer 3
DC1	Product 1	12	15	13
	Product 2	15	14	13
	Product 3	16	15	16
DC 2	Product 1	14	16	18
	Product 2	12	15	15
	Product 3	18	17	12
DC 3	Product 1	19	17	16
	Product 2	18	16	15
	Product 3	14	12	15

Various ranges of Federal CO_2 prices for rule-makings, by discount rate are shown in Table 3.4.13 and Figure 3-12 (EPA, 2015a). Based on this data, in this research, the carbon cost (the parameter of θ) was set to $50/ton CO_2 in the objective function.

Table 3.4.1: Range of Federal CO_2 Prices for Rulemakings, by discount rate (in 2007 Dollars per metric ton CO_2)

	Discount Rate and Statistic			
Year	5% Average	3% Average	2.5% Average	3% 95th percentile
2015	$11	$36	$56	$105
2020	$12	$42	$62	$123
2025	$14	$46	$68	$138
2030	$16	$50	$73	$152
2035	$18	$55	$78	$168
2040	$21	$60	$84	$183
2045	$23	$64	$89	$197
2050	$26	$69	$95	$212

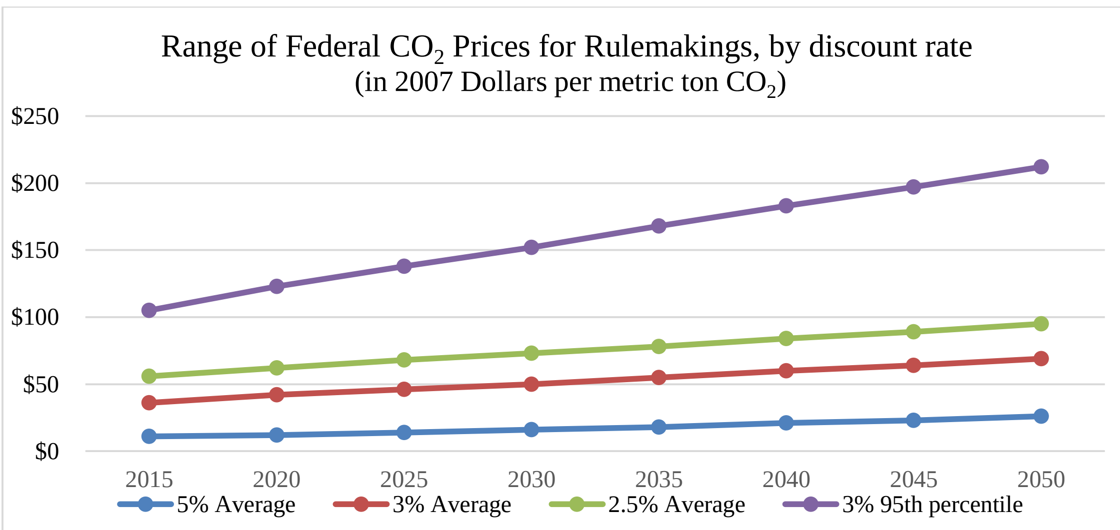

Figure 3-12: Various ranges of Federal CO_2 prices for 2015-2050

Moreover, the value of parameter CO_2 allowed was set at 900 tons (that is, the carbon dioxide emission allowance, and has been allocated by the government) (Agency, I.E., 2015). The value of parameter μ_o, which is a CO_2 emission factor of a facility, measured in tons per kWh of operation, was assumed to be equal to 0.0008. The value of parameter μ_{tr}, which refers to CO_2 emission factor for transportation in tons per mile per unit, was assumed to be equal to 0.00001 (Agency, I.E., 2015).

At first we solved the coded proposed mathematical modeling in Lingo software and we set the value of maximum service levels for each period equal to 1 and increased the minimum value of service levels $SL_{i,r,t}^{min}$ starting from 0 (step size 0.1) for each period at each iteration. We found that the coded model in Lingo software can be solved for various ranges of minimum service levels from 0 to 0.7 and holding the value of 1 for maximum service levels, but when we set the value of minimum service levels equal to 0.8, the model became infeasible and couldn't be solved by Lingo. Considering that, we decided to code and run the proposed model in MATLAB (version R2014b) for "FminCon optimization solver" and "Grey Wolf Optimizer algorithm". In order to have fair comparisons we set the value of maximum service levels for each of periods equal to 1 and the value of minimum service levels for each period equal to 0.7 and 1 and achieved the results.

Using Lingo software, the local optimum solution found at iteration 50,399. Elapsed time was equal to 1,500 seconds. The best value of the objective function (total supply chain costs and CO_2 costs) achieved equal to 1,109,627 in dollars and the amount of current emitted carbon dioxide (CO_2) is equal to 1,414.58 in tonnages (CO_2 costs is 25,728 in dollars). Figure 3-13 shows the achieved results by Lingo software and the related initial setting.

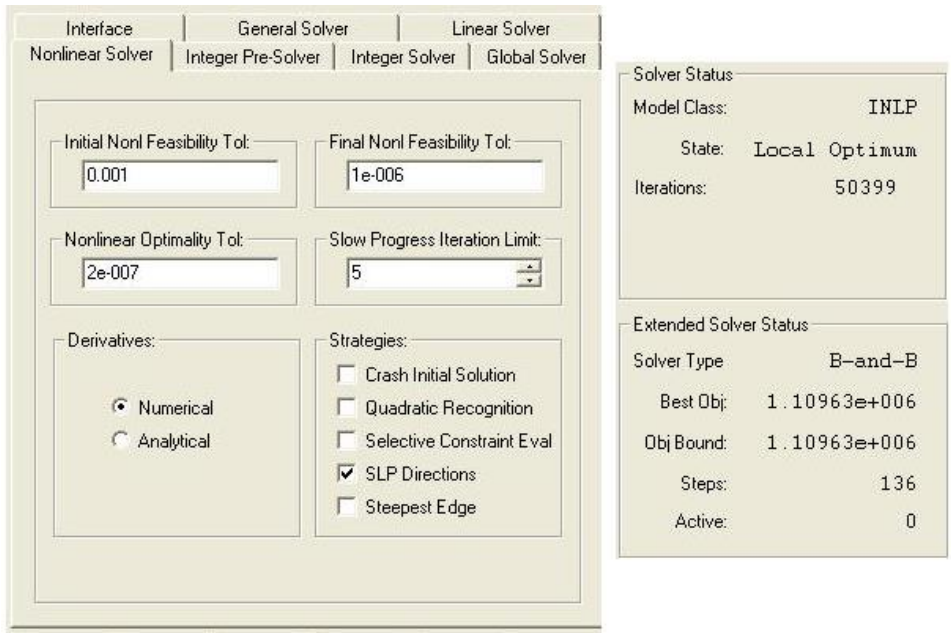

Figure 3-13: Achieved result by Lingo software and the related initial setting

Then, we generated five different initial random sets in order to solve the proposed mathematical modeling by the other aforementioned two methods. Using Lingo software, we achieved the same solution, which mentioned earlier, for all of these initial random sets.

We coded the proposed nonlinear model in MATLAB software (version R2014b) and “FminCon” optimization tool was applied to achieve the best solution. At first, we achieved the best solution for a condition that the value of parameter $SL_{i,r,t}^{min}$ is equal to 0.7 and the maximum service levels is equal to 1 in each periods. Then, we solved the model for a situation in which both of the values of parameter $SL_{i,r,t}^{min}$ and maximum service levels are equal to 1 in each period. Results are shown in Tables 3.4.14 and 3.4.15. Tolerances and stopping criteria are set as follows:

- X tolerance is set at 1E-10.
- Function tolerance is set at 1E-6.
- The nonlinear tolerance constraint is set at 1E-6.
- The minimum perturbation is set at 0 and maximum perturbation is set at Inf.
- The maximum function evaluation is set at 9,000,000 and maximum iteration set at 4,000.
- The LDL factorization is selected as a sub-problem algorithm.
- The Broyden Fletcher Goldfarb Shanno (BFGS) algorithm is selected for Hessian calculations.

Table 3.4.2: Achieved results by FminCon optimization solver (minimum service levels 0.7, maximum service levels 1)

Random set#	Elapsed time (sec)	Objective function[8] value ($)	CO_2 emissions	CO_2 Penalty Cost ($)	Iterations
1	1,846	2,142,134	1,432.65	26,632	4,000
2	870	2,161,830	1,427.90	26,393	4,000
3	1,666	2,196,788	1,433.12	26,656	4,000
4	1,666	1,978,652	1,429.20	26,459	4,000
5	1,222	2,089,723	1,429.64	26,481	4,000

Table 3.4.3: Achieved results by FminCon optimization solver (minimum service levels 1, maximum service levels 1)

Random set#	Elapsed time (sec)	Objective function value ($)	CO_2 emissions	CO_2 Penalty Cost ($)	Iterations
1	1,820	2,395,792	1,438.43	26,921	4,000
2	924	2,283,104	1,429.72	26,486	4,000
3	937	2,524,225	1,438.81	26,930	4,000
4	1,796	2,012,723	1,430.98	26,548	4,000
5	806	2,257,461	1,433.14	26,656	4,000

[8] Objective function value refers to the total supply chain costs and CO_2 costs.

Then, using the same initial random sets (generated earlier) and same conditions for minimum and maximum service levels, we coded the proposed mathematical modeling in Matlab and utilized Grey Wolf Optimizer approach. At first, we used the same number of iterations (4,000) used for FminCon optimization method and found that the solution didn't converge. So, we increased the number of iterations and found that it will converge after 10,000 iterations. Results are shown in Tables 3.4.16 and 3.4.17.

Based on the achieved result by FminCon optimization solver and Grey Wolf Optimizer algorithm, when the value of $SL_{i,r,t}^{min}$ for $\forall i, r, t$ (these values are set by retailers) increases, consequently the value of the objective function (total costs of the supply chain network which also contains carbon emissions costs) increase as well. Here, it can be inferred that increasing the minimum service levels and meeting more portions of customers' demands are accompanied by increasing the related costs for preparing the required products and decreasing the penalty costs of backordered products. The result also verifies that the amount of increased costs related to preparing the products and meeting customers' demand outweighs the decreased penalty costs related to decreased amount of backordered products.

Table 3.4.4: Achieved results by Grey Wolf Optimizer algorithm (minimum service levels 0.7, maximum service levels 1)

Random set#	Elapsed time (sec)	Objective function[9] value ($)	CO_2 emissions	CO_2 Penalty Cost ($)	Iterations
1	757	336,582	1,407.54	25,375	10,000
2	835	360,560	1,408.46	25,423	10,000
3	746	331,304	1,408.18	25,409	10,000
4	780	321,374	1,407.68	25,384	10,000
5	782	405,309	1,407.41	25,370	10,000

[9] Objective function value refers to the total supply chain costs and CO_2 costs.

Table 3.4.5: Achieved results by Grey Wolf Optimizer algorithm (minimum service levels 1, maximum service levels 1)

Random set#	Elapsed time (sec)	Objective function[10] value ($)	CO_2 emissions	CO_2 Penalty Cost($)	Iterations
1	733	370,931	1,408.66	25,432	10,000
2	763	456,402	1,407.46	25,373	10,000
3	763	374,643	1,408.01	25,400	10,000
4	763	354,568	1,407.61	25,380	10,000
5	784	474,135	1,408.35	25,417	10,000

The achieved results by FminCon Solver, Grey Wolf algorithm, and Lingo Branch and Bound algorithm are compared in Tables 3.4.18 and 3.4.19, and Figure 3-14. The order of achieved objective function are different and it can be concluded that the standard deviation or the parameter of range/average has a better value in achived results by FminCon Solver in comparison to Grey Wolf Optimizer algorithm. It shows that the achieved results by the Grey Wolf Optimizer algorithm in comparison to FminCon solver and Lingo Branch and Bound algorithm are more sensitive toward the initial value of the starting point (initial random sets).

However, the speed of Grey Wolf Optimizer in finding the local optimums is more than the FminCon Solver and Lingo Branch and Bound algorithm. The other point is that, the convergence in FminCon Solver (4,000 iterations) occurs sooner than the Grey Wolf algorithm (at least 10,000).

For all methods, increasing the minimum service levels from 0.7 to 1 has been accompanied by an increase in the achieved objective function. Moreover, we depicted the Amount of products dispatched from assemblers to distribution centers as a sample

[10] Objective function value refers to the total supply chain costs and CO_2 costs.

achieved decision variable for these three different method when minimum service level is equal to 0.7 and maximum service level sets at 1 and we can evaluate and analyze how much the ordering system is smooth and leveled for each of methods. This indicator can also be considered as one of the important key factors in our comparisons (Figuers 3-15 to 3-17). Considering the achieved results, we can say that each of applied methods has their own capability in finding the best solution and evaluation.

- Lingo Branch and Bound algorithm can give us a solution that is not sensitive toward the initial random sets, but it is a local optimum and cannot guarantee that it is the best solution and we cannot increase the value of minimum service level more than 0.7 and we receive the message of being infeasible.
- The FminCon solver can give us solutions that are somehow depends on the initial random sets but in comparison to the Grey wolf optimizer algorithm they are less sensitive. The objective function converges to a definite value sooner than the Grey wolf optimizer algorithm.
- The Grey wolf optimizer algorithm gives us solutions that have a better value for the objective function as the main objective is minimizing that but they are very sensitive toward initial random sets and the objective function cannot converge to a specific value for iterations less than 10,000.

Table 3.4.6: Comparing the results of FminCon Solver and the Grey Wolf algorithm for (SLmin=0.7, SLmax=1)

	FminCon (SLmin=0.7, SLmax=1)	Grey Wolf (SLmin=0.7, SLmax=1)
Average	2113825	351026
Range	218136	83935
Range/average	0.103	0.239

Table 3.4.19: Comparing the results of FminCon Solver and Grey Wolf algorithm for (SLmin=1, SLmax=1)

	FminCon (SLmin=1, SLmax=1)	Grey Wolf (SLmin=1, SLmax=1)
Average	2294661	406336
Range	511503	119567
Range/average	0.223	0.294

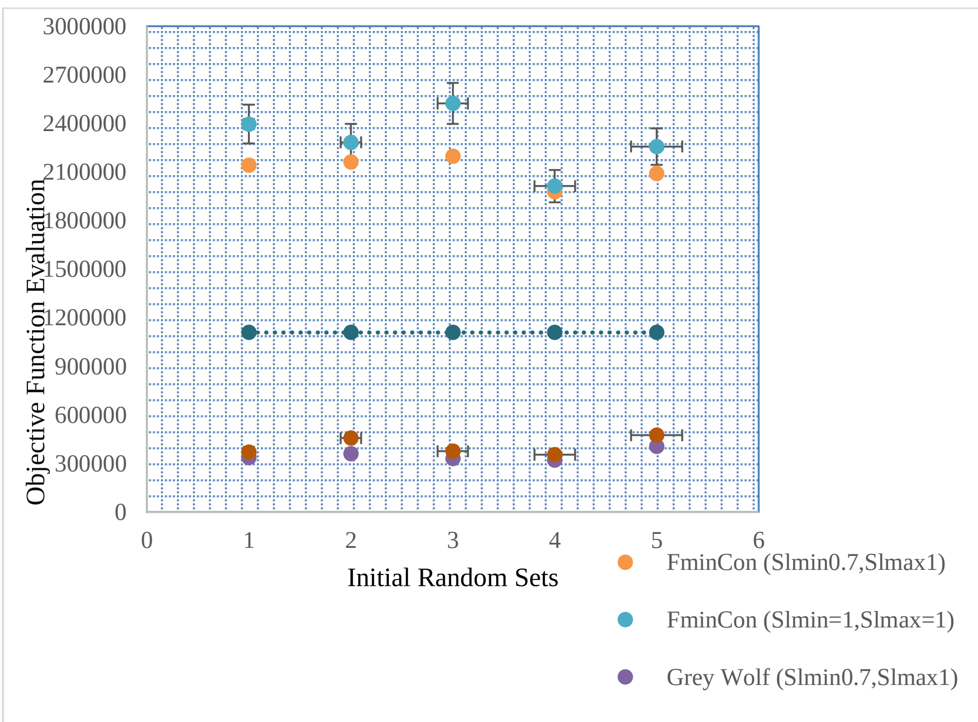

Figure 3-14: Comparing the achieved results for the objective function value by FminCon solver, Grey Wolf algorithm, and Lingo Branch and Bound algorithm

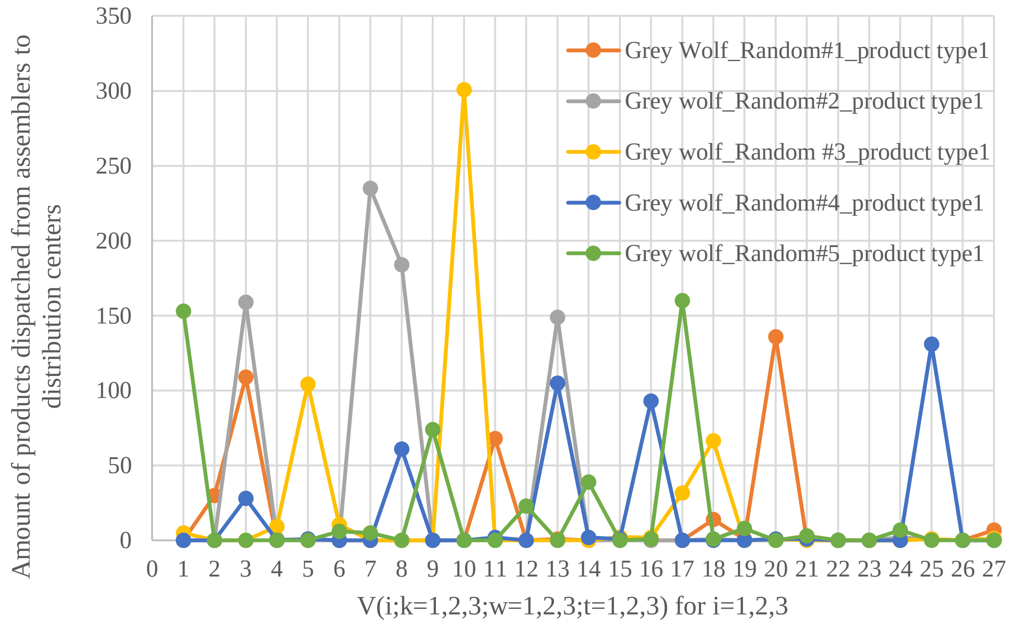

Figure 3-15: Achieved amount of ordering for products that should be dispatched from assembling sites to distribution site by Grey Wolf Optimizer algorithm

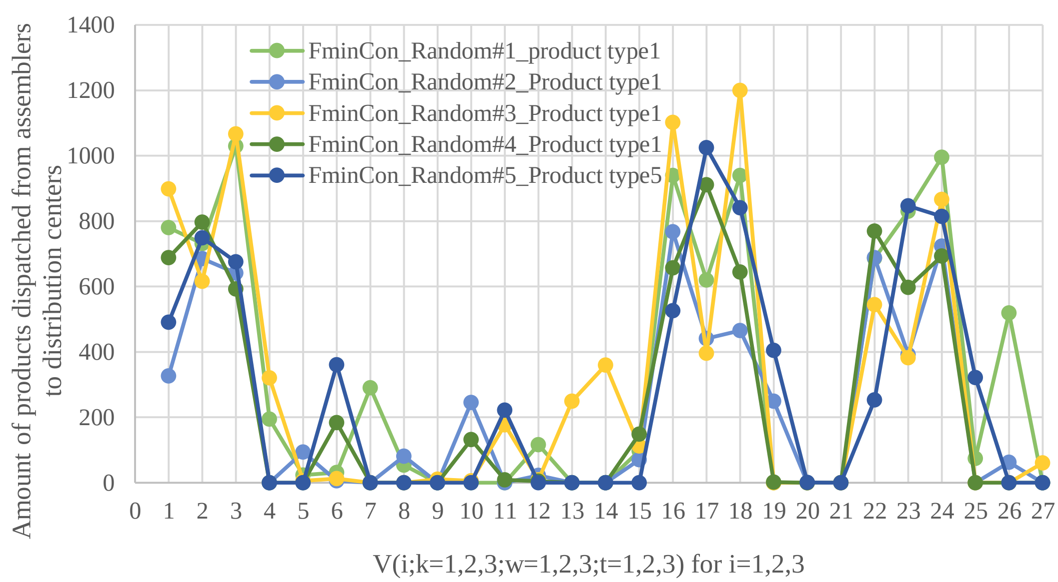

Figure 3-16: Achieved amount of ordering for products that needs to be dispatched from assembling sites to distribution site by the FminCon solver

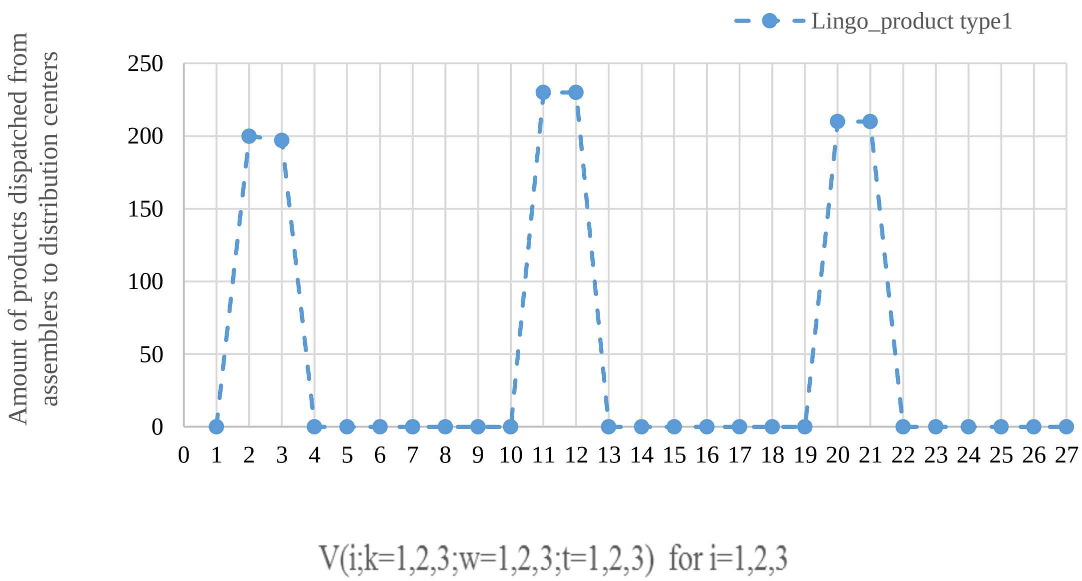

Figure 3-17: Achieved amount of ordering for products that needs to be dispatched from assembling sites to distribution site by Lingo Branch and Bound algorithm

All of the achieved results by FminCon solver and Grey Wolf Optimizer algorithm are shown in Figures 3-18 to 3-57.

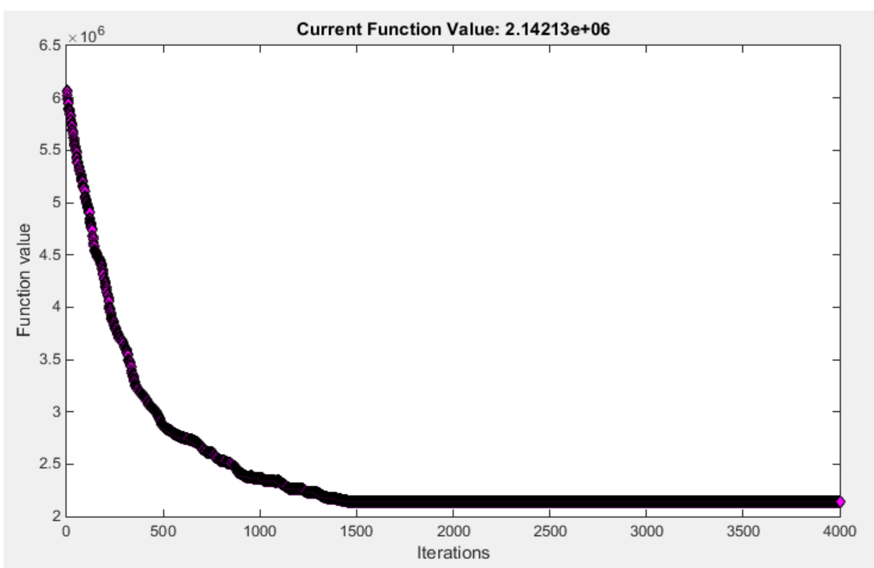

Figure 3-18: Achieved current function value for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#1)

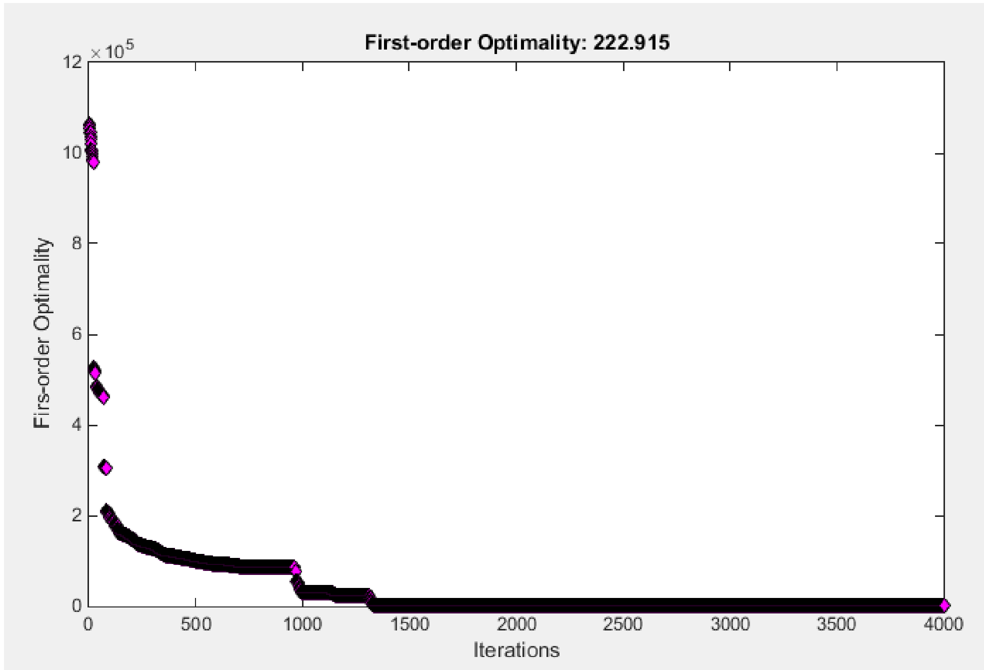

Figure 3-19: Achieved first-order optimality for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#1)

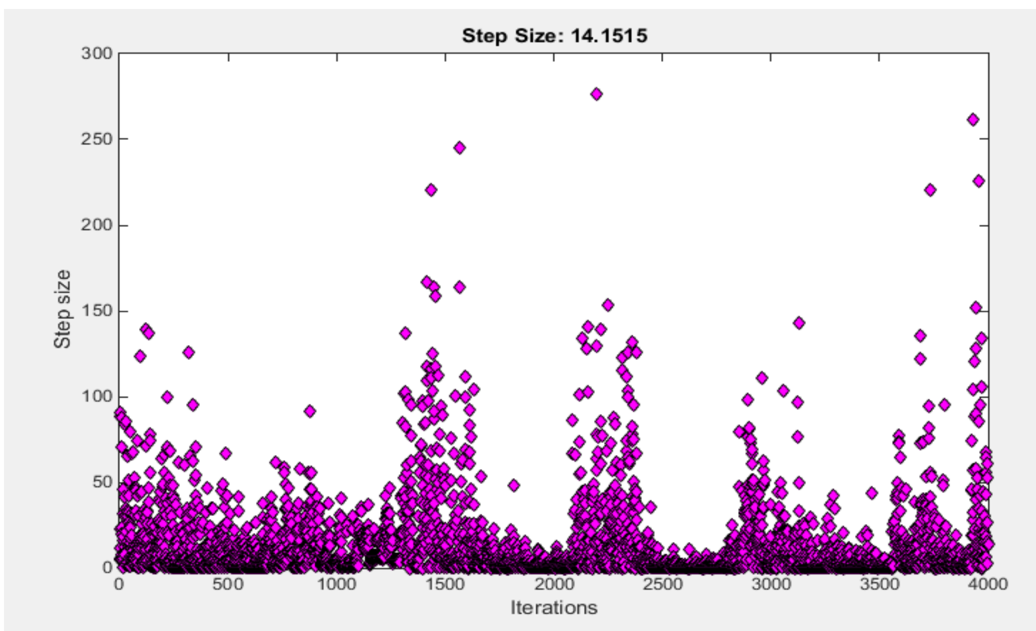

Figure 3-20: Diagram of step size for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#1)

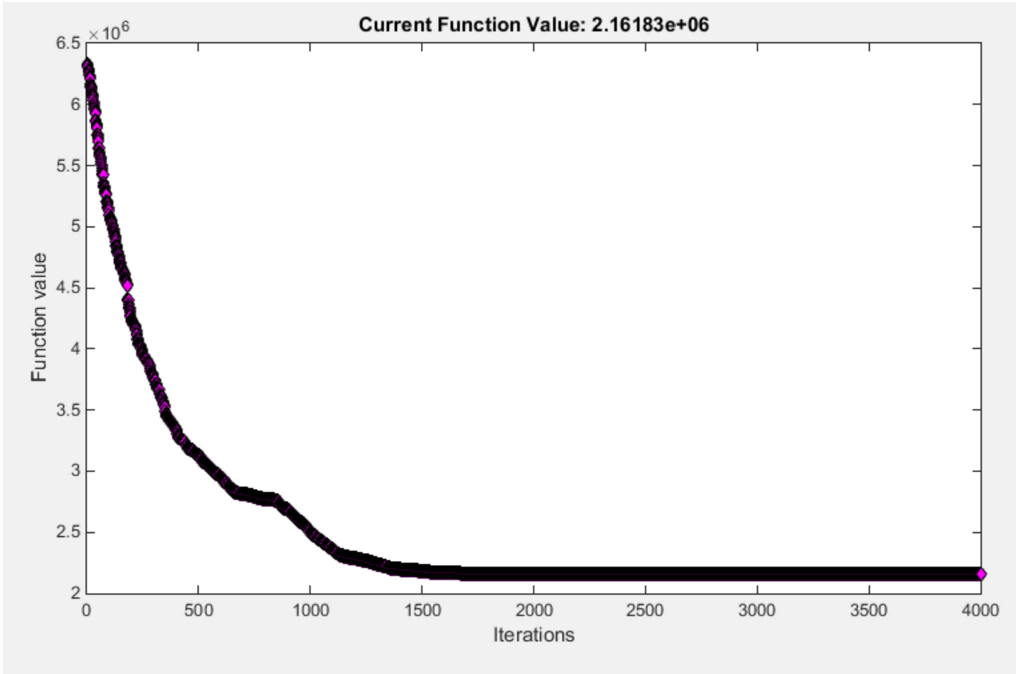

Figure 3-21: Achieved current function value for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#2)

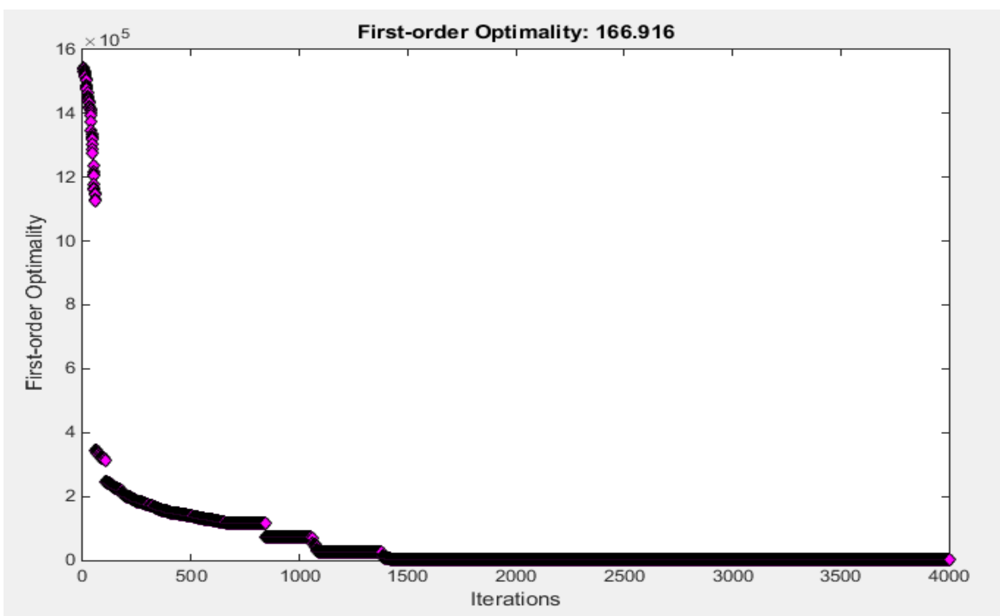

Figure 3-22: Achieved first-order optimality for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set# 2)

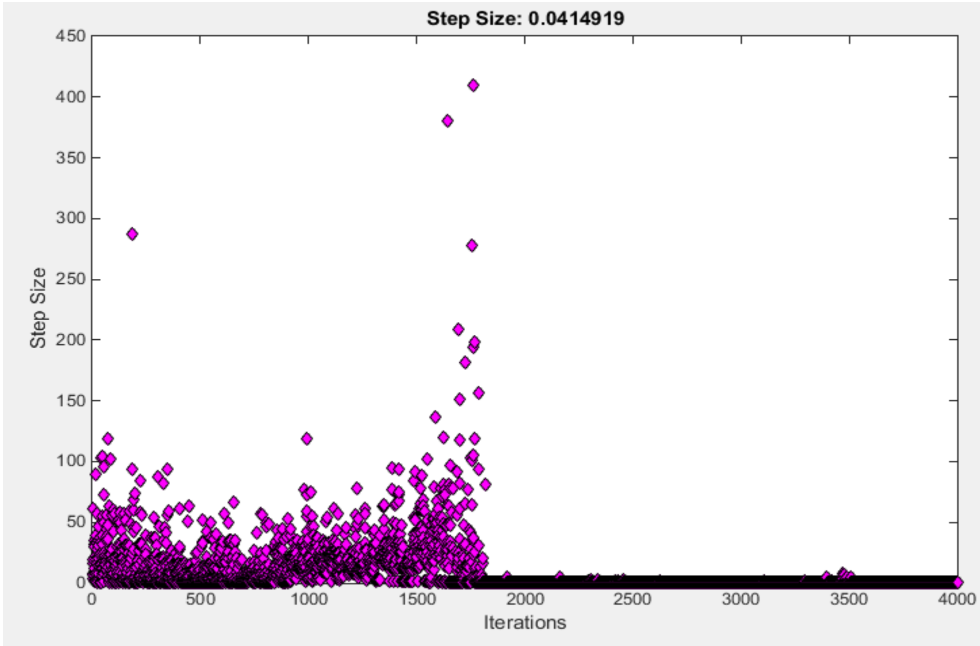

Figure 3-23: Diagram of step size for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#2)

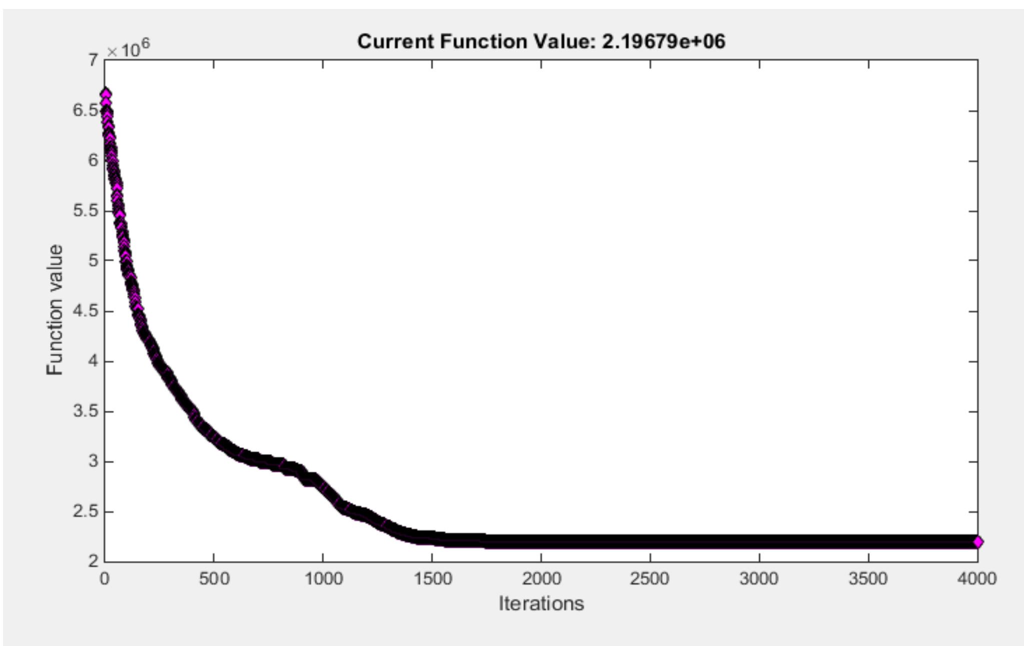

Figure 3-24: Achieved current function value for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#3)

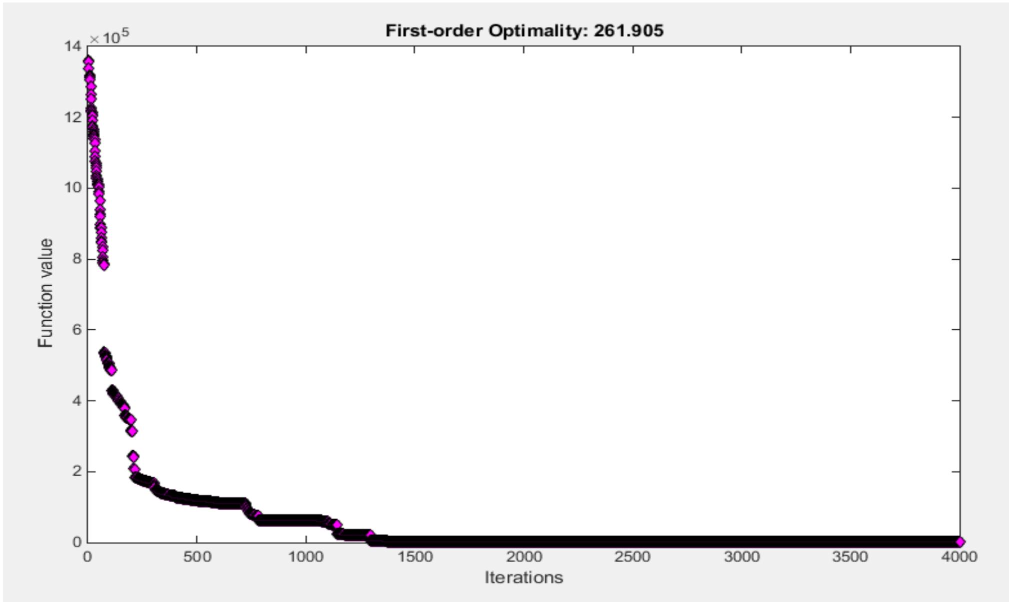

Figure 3-25: Achieved first-order optimality for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#3)

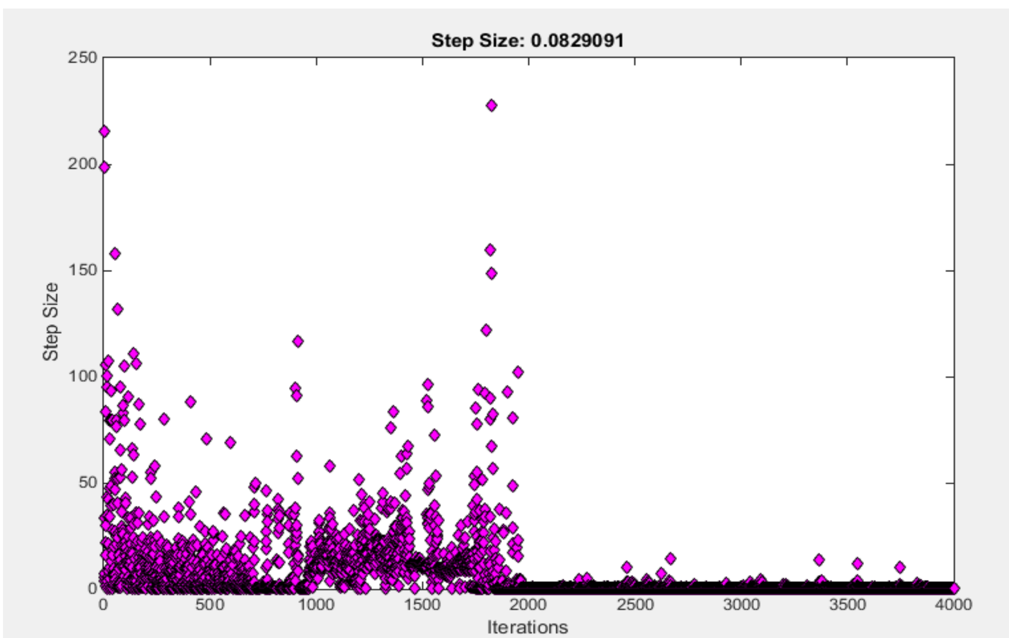

Figure 3-26: Diagram of step size for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#3)

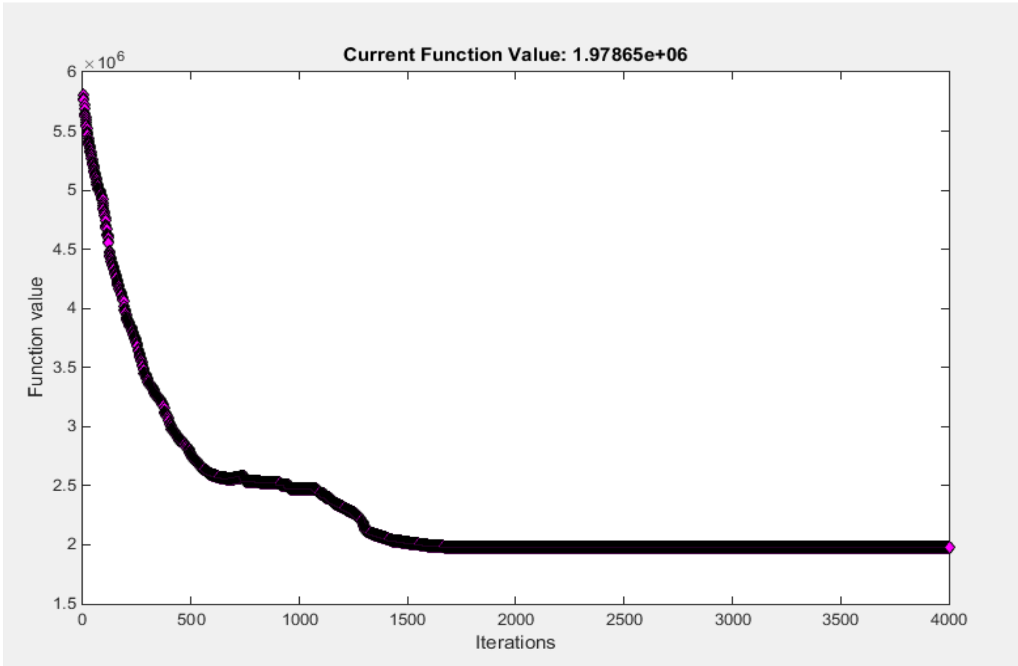

Figure 3-27: Achieved current function value for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#4)

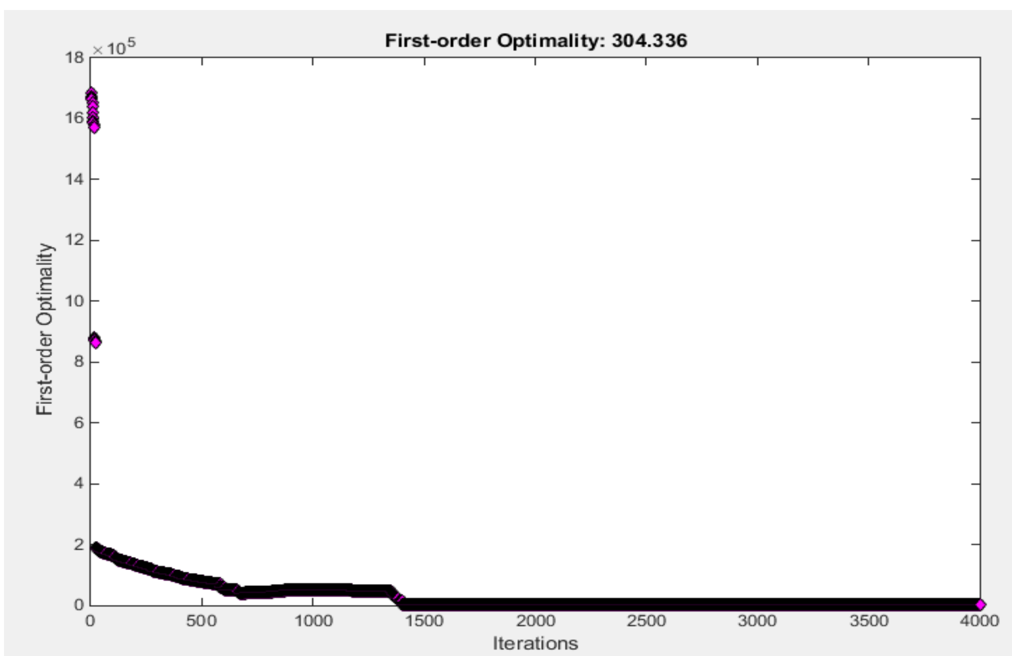

Figure 3-28: Achieved first-order optimality for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#4)

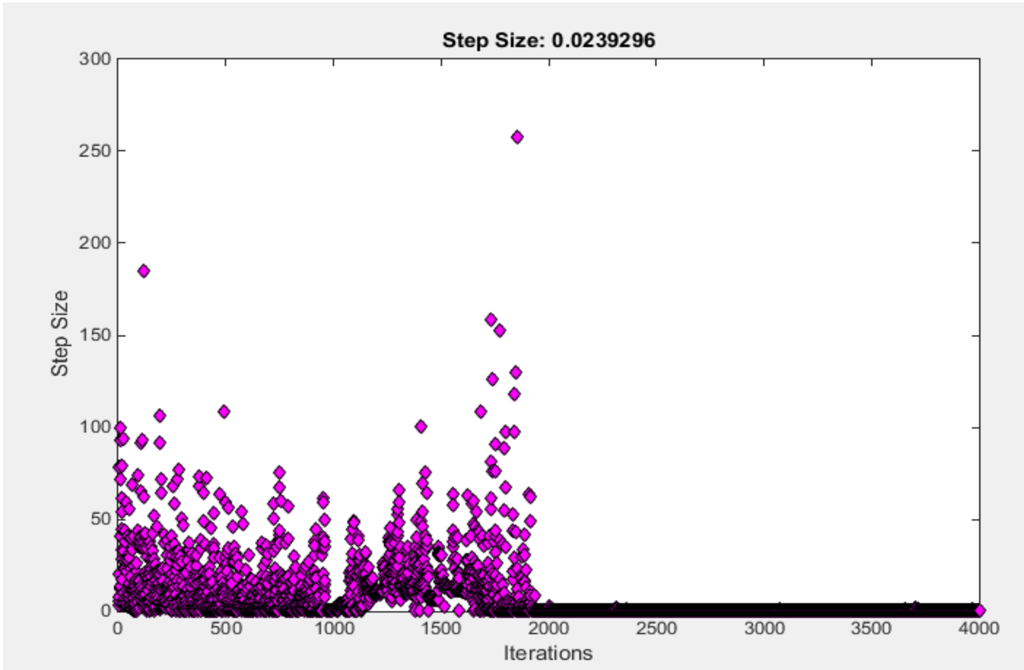

Figure 3-29: Diagram of step size for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#4)

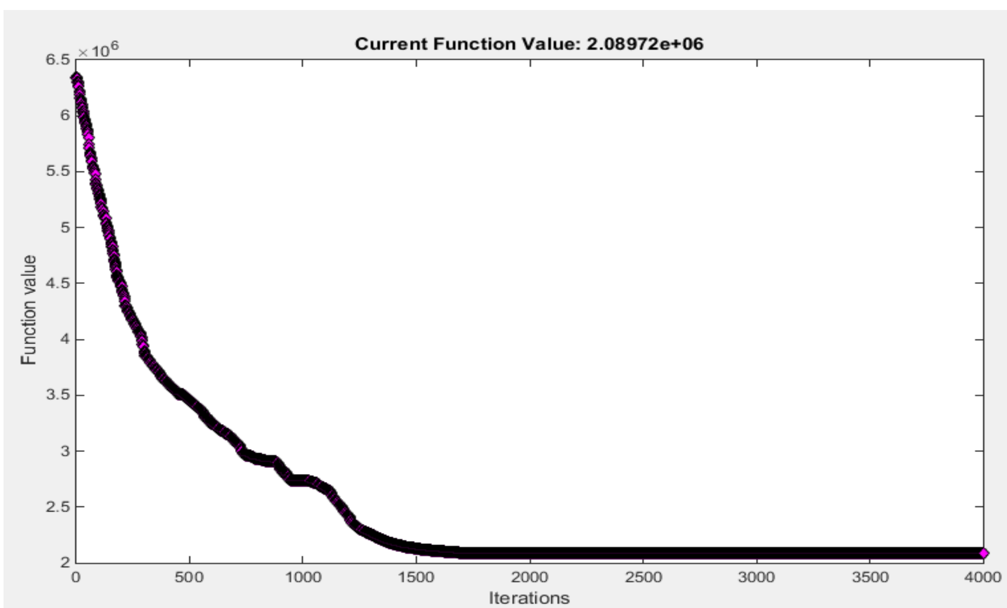

Figure 3-30: Achieved current function value for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#5)

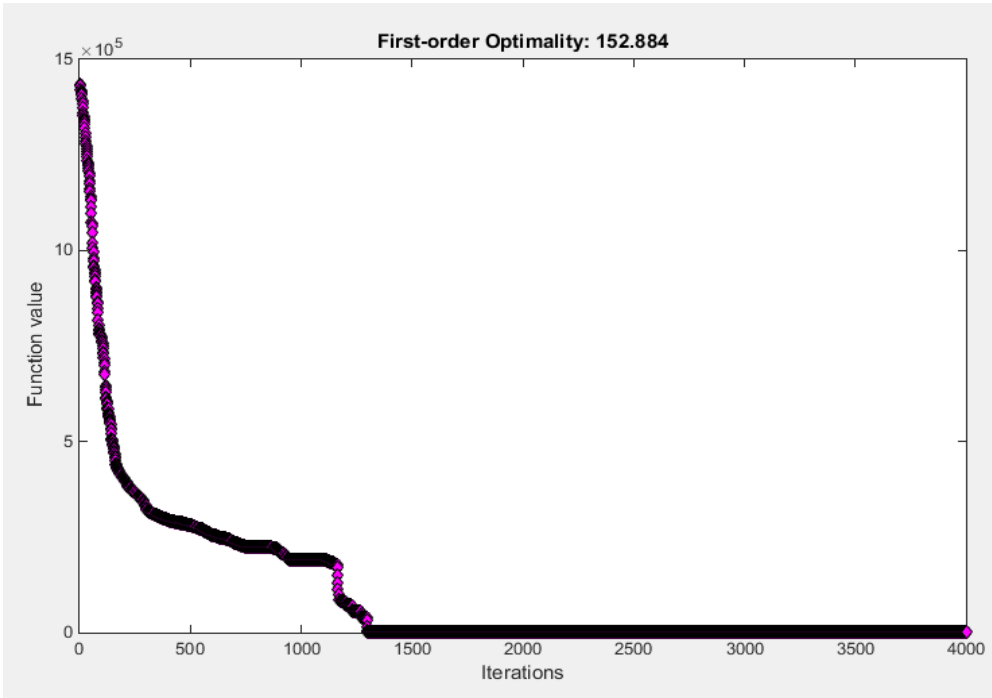

Figure 3-31: Achieved first-order optimality for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#5)

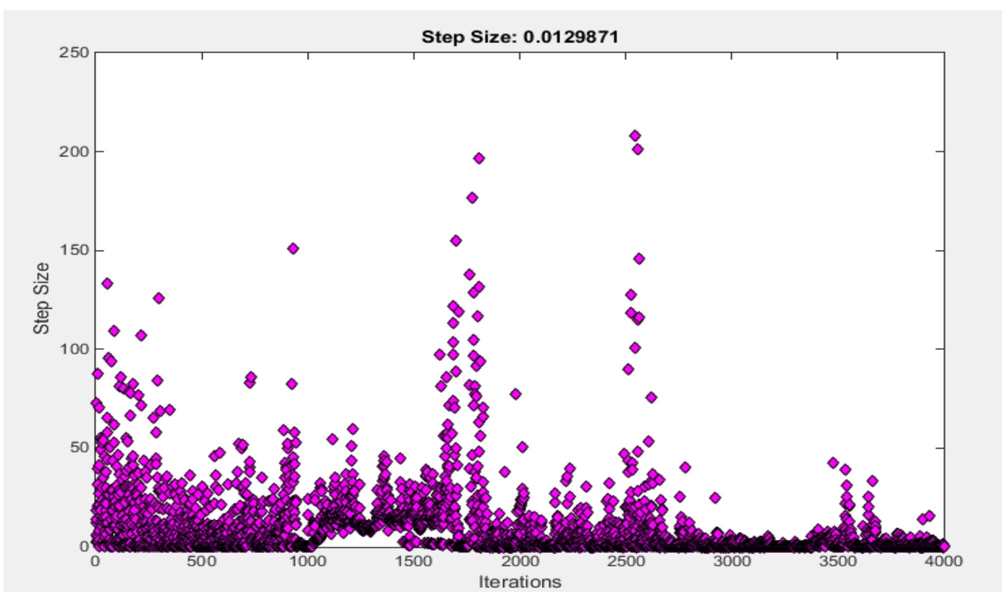

Figure 3-32: Diagram of step size for the best solution found by FminCon (minimum service level 0.7, maximum service level 1, Random set#5)

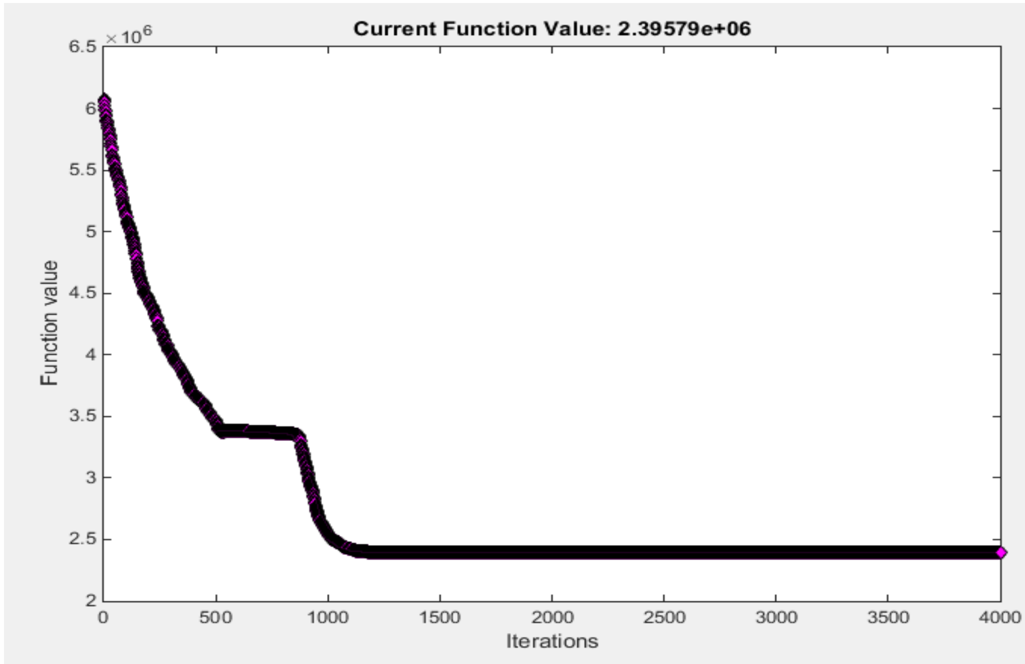

Figure 3-33: Achieved current function value for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#1)

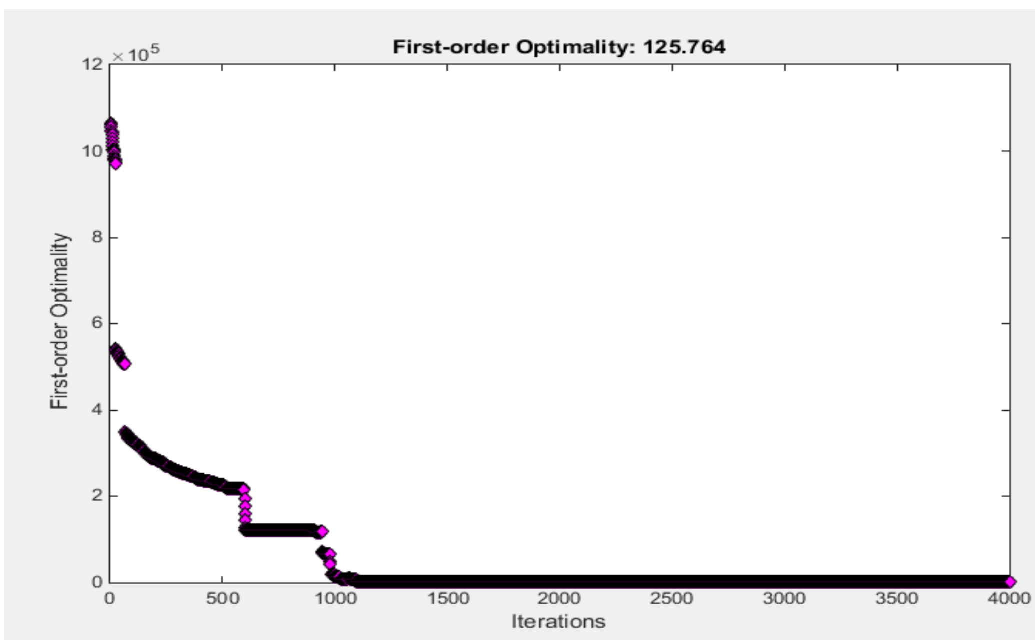

Figure 3-34: Achieved first-order optimality for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#1)

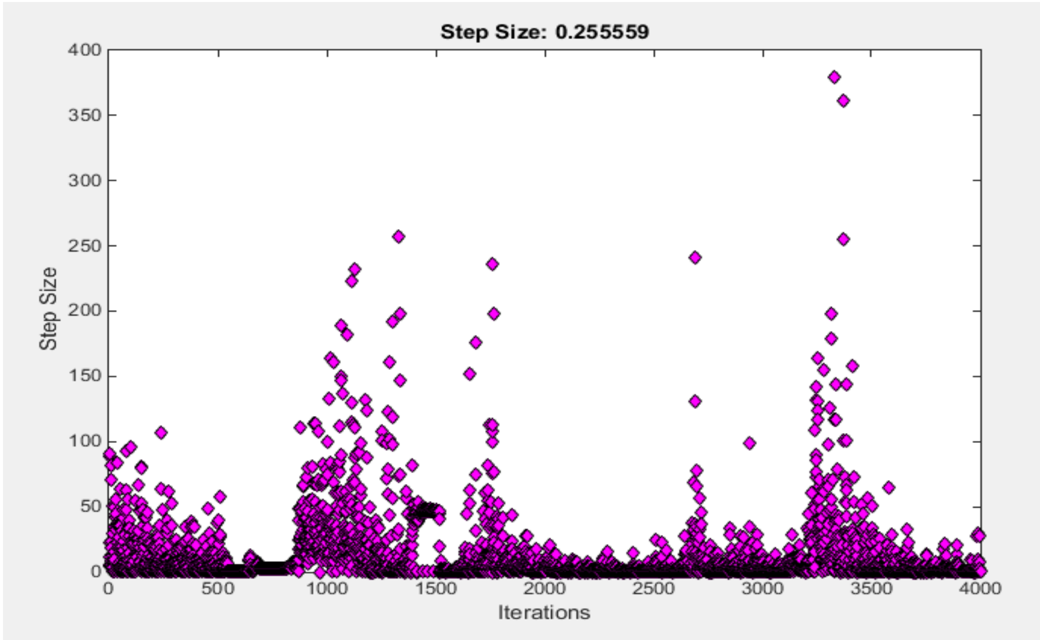

Figure 3-35: Diagram of step size for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#1)

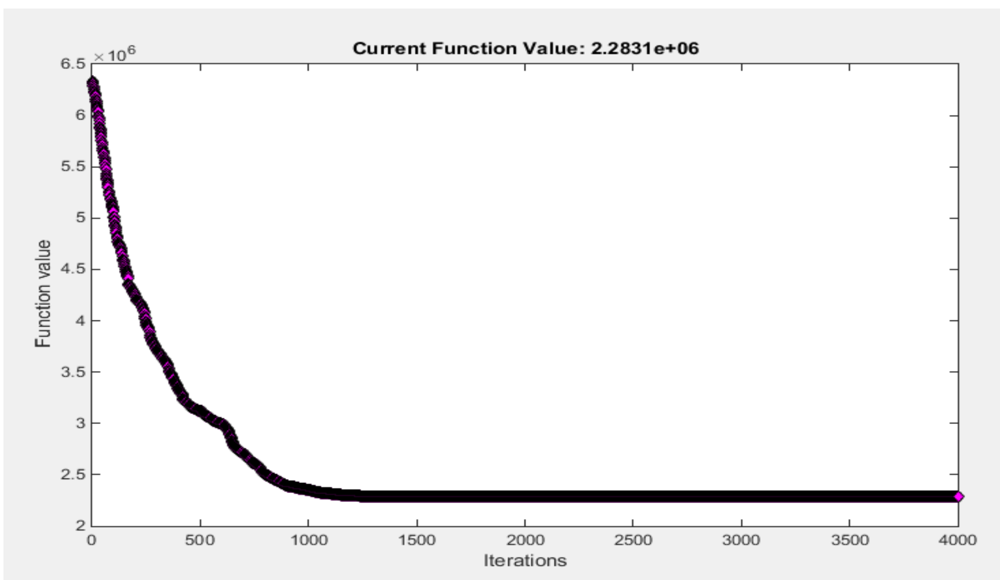

Figure 3-36: Achieved current function value for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#2)

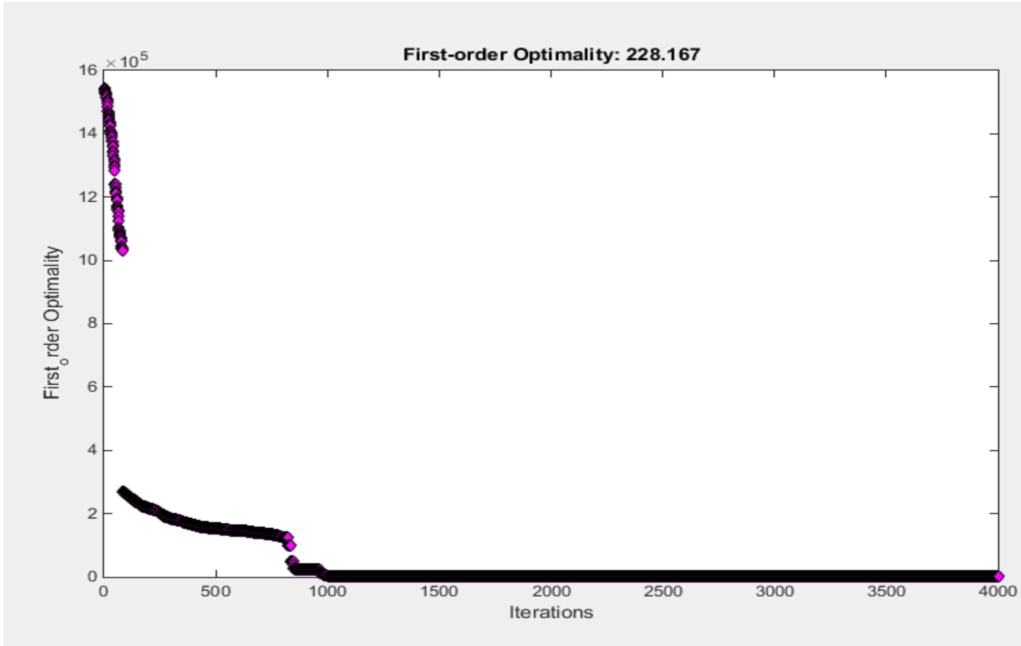

Figure 3-37: Achieved first-order optimality for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#2)

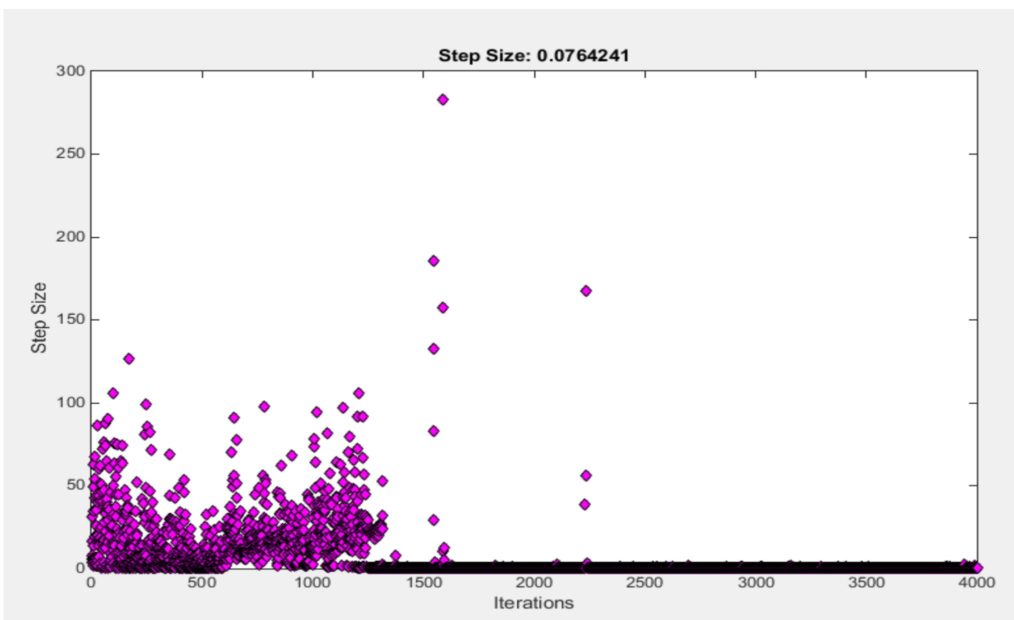

Figure 3-38: Diagram of step size for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#2)

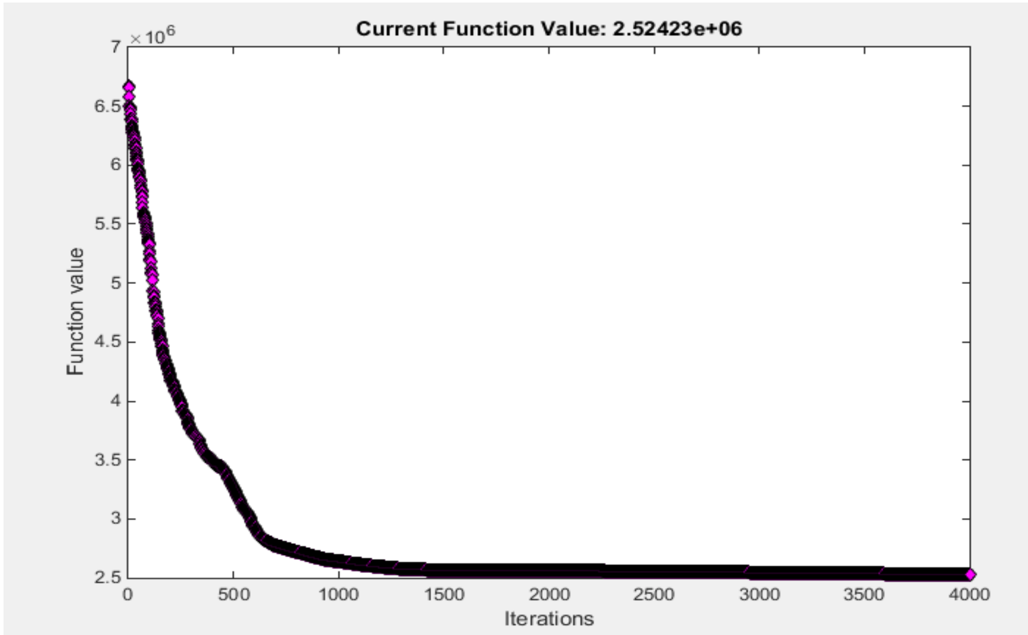

Figure 3-39: Achieved current function value for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#3)

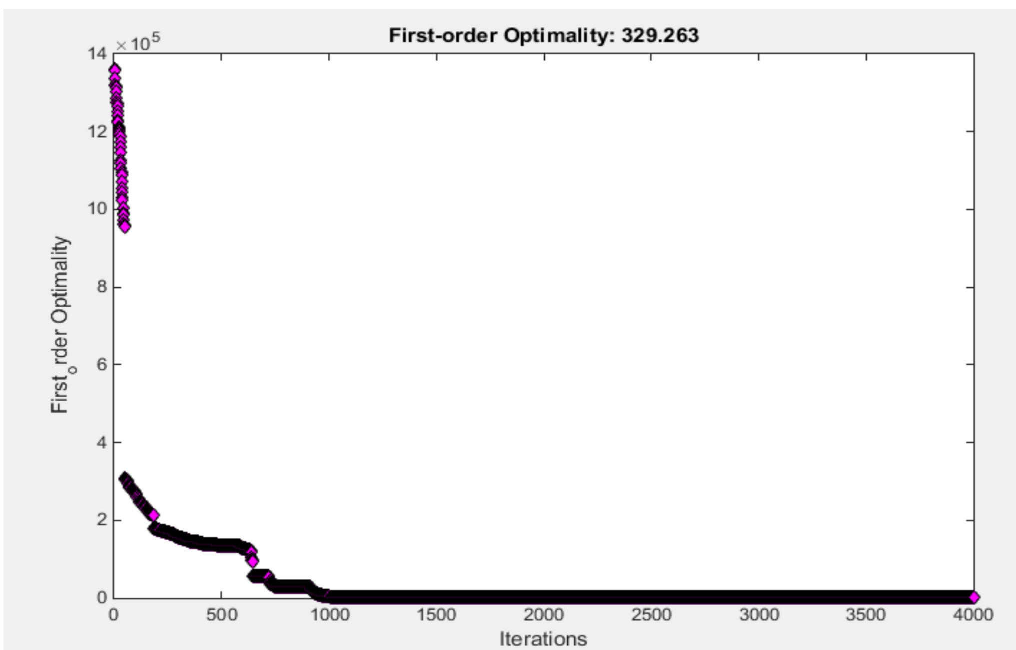

Figure 3-40: Achieved first-order optimality for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#3)

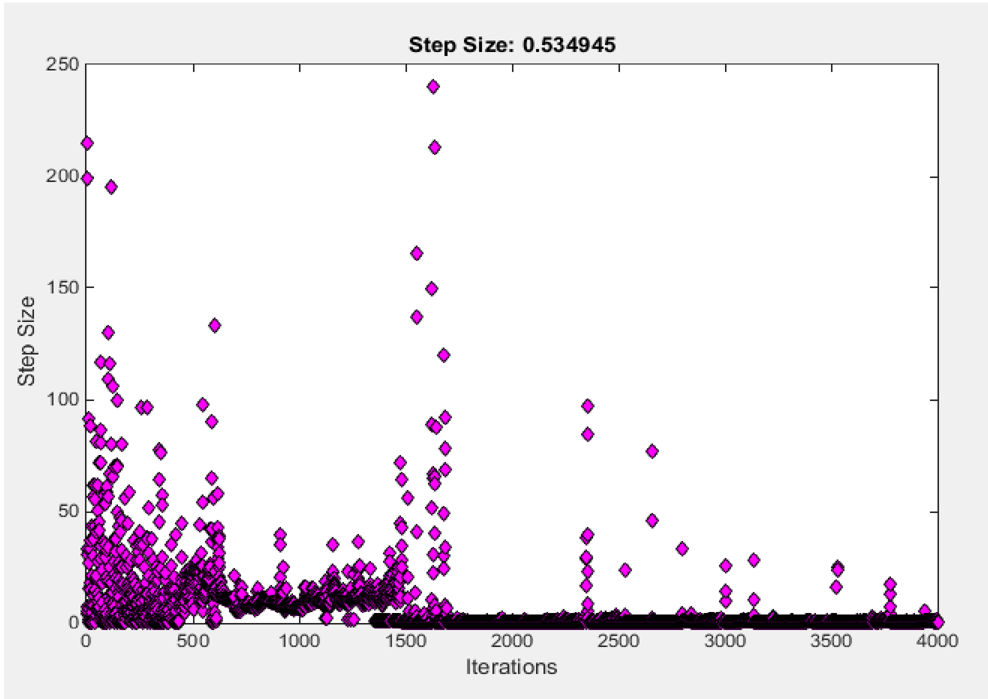

Figure 3-41: Diagram of step size for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#3)

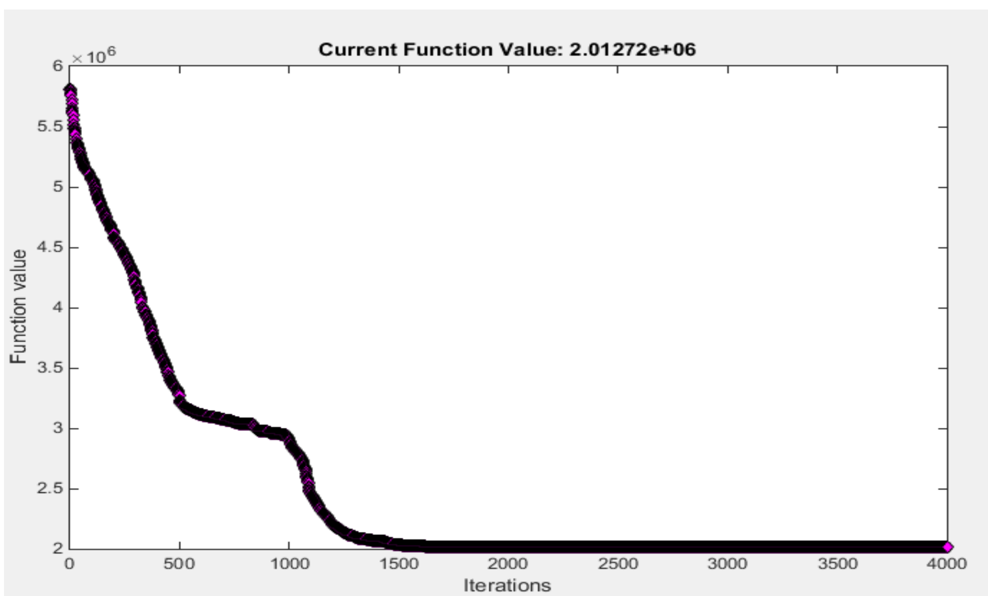

Figure 3-42: Achieved current function value for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#4)

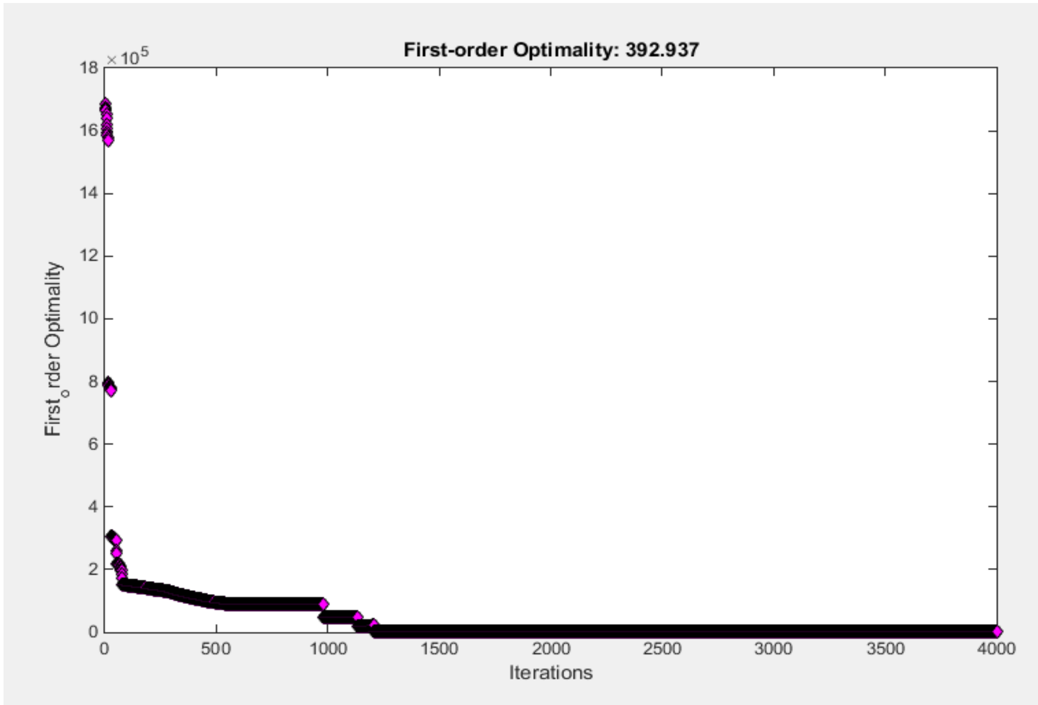

Figure 3-43: Achieved first-order optimality for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#4)

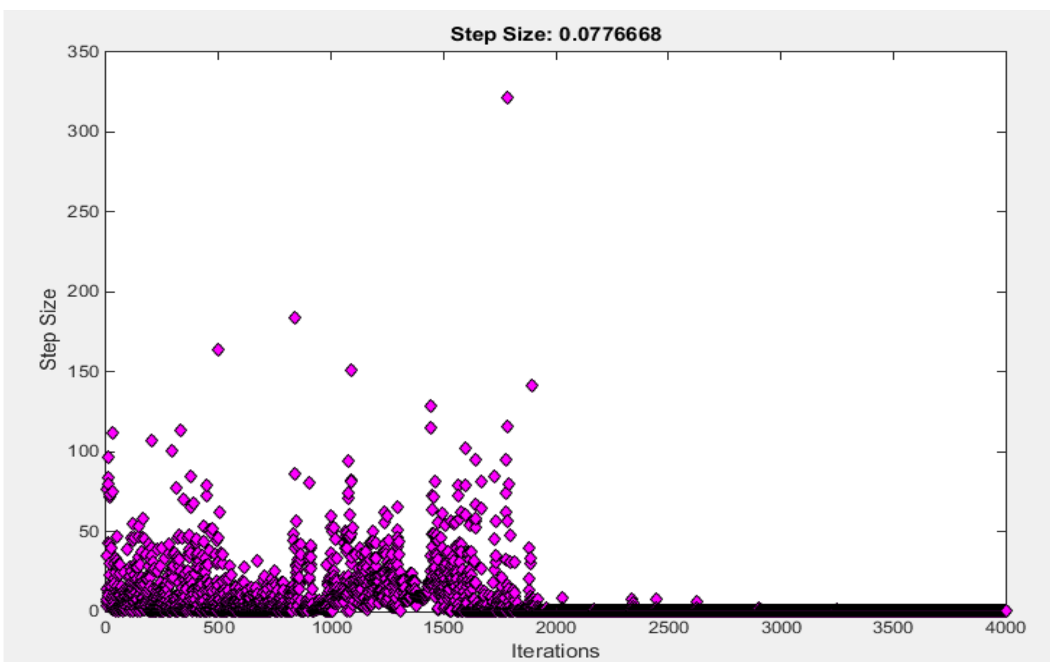

Figure 3-44: Diagram of step size for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#4)

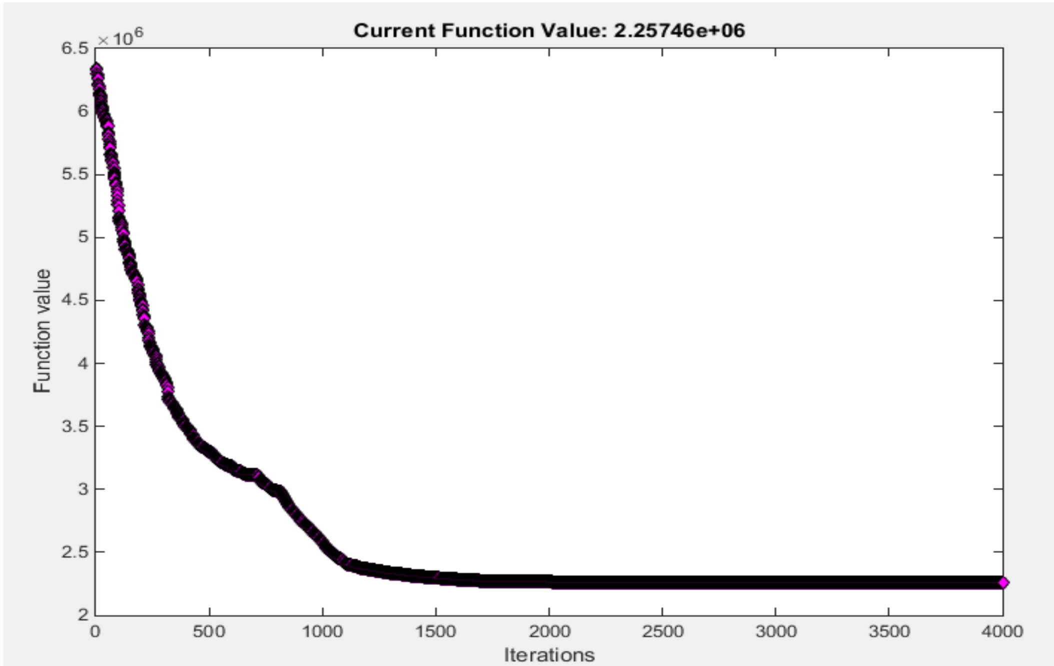

Figure 3-45: Achieved current function value for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#5)

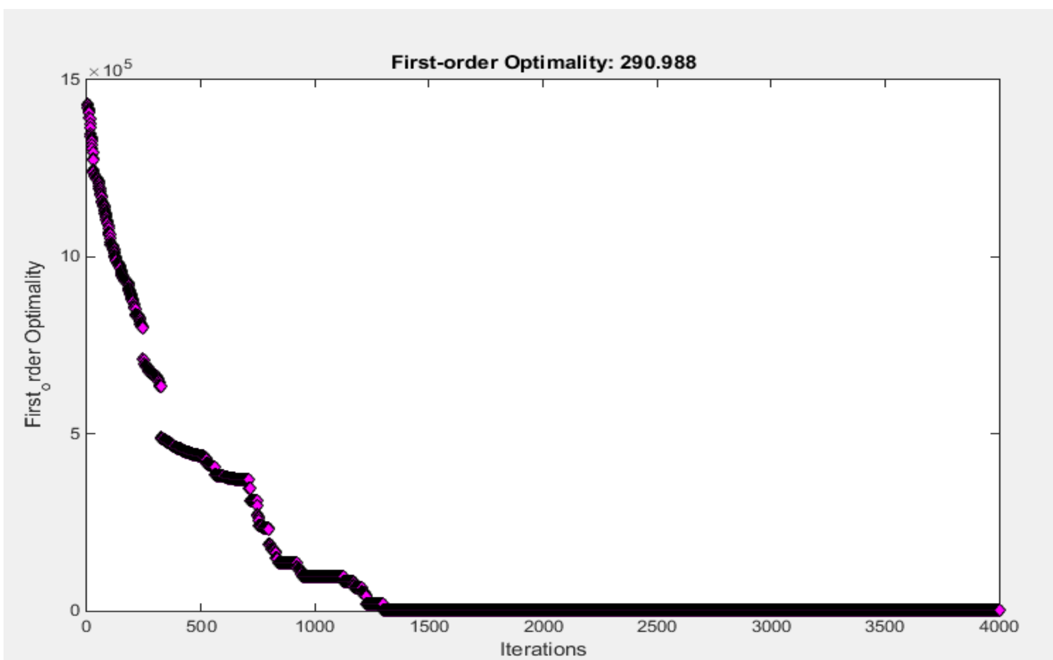

Figure 3-46: Achieved first-order optimality for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#5)

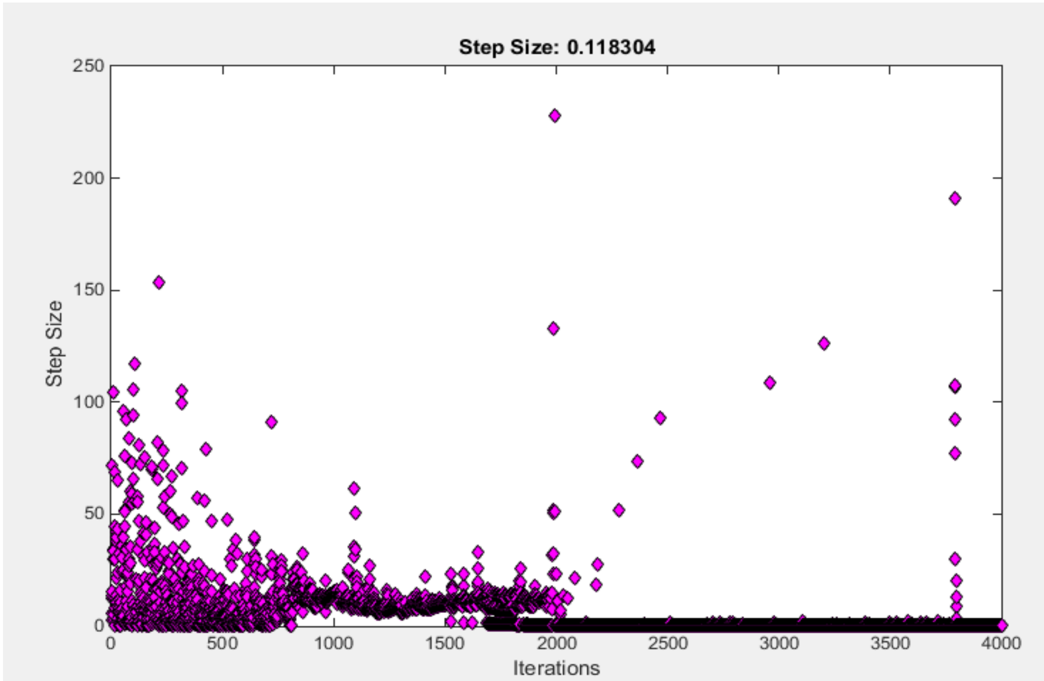

Figure 3-47: Diagram of step size for the best solution found by FminCon (minimum service level 1, maximum service level 1, Random set#5)

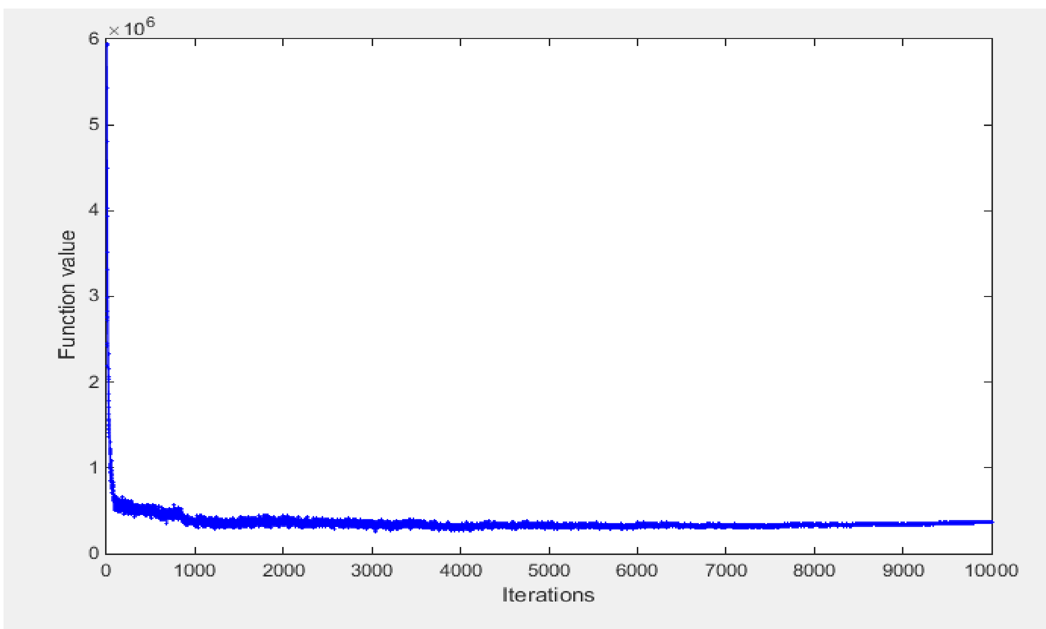

Figure 3-48: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 0.7, maximum service level 1, Random set#1)

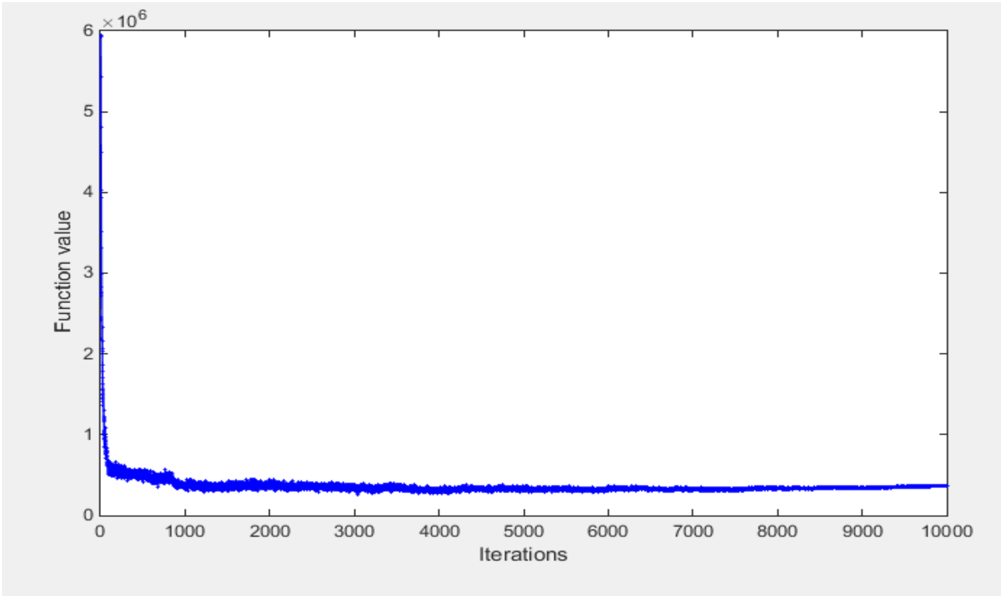

Figure 3-49: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 0.7, maximum service level 1, Random set#2)

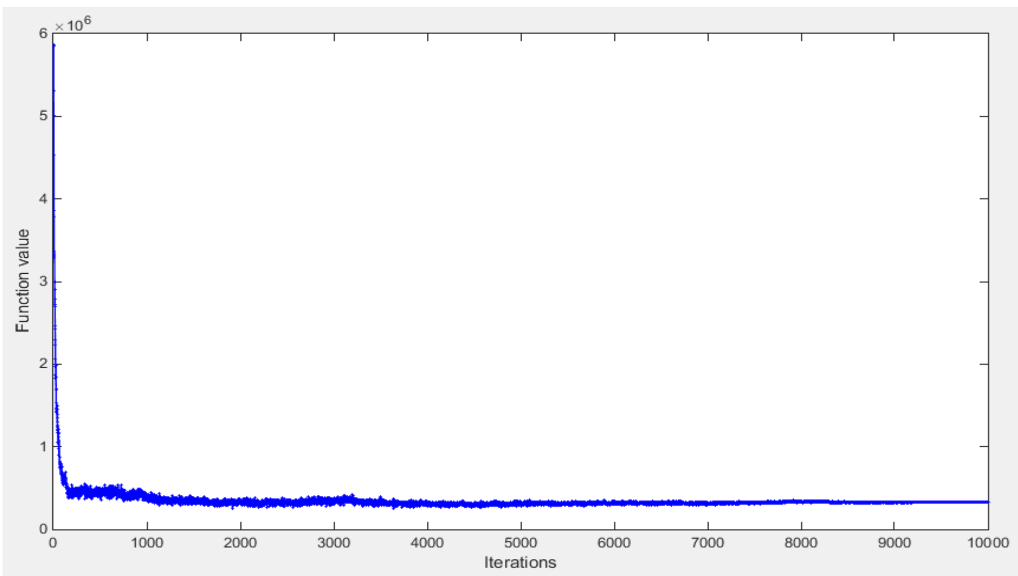

Figure 3-50: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 0.7, maximum service level 1, Random set#3)

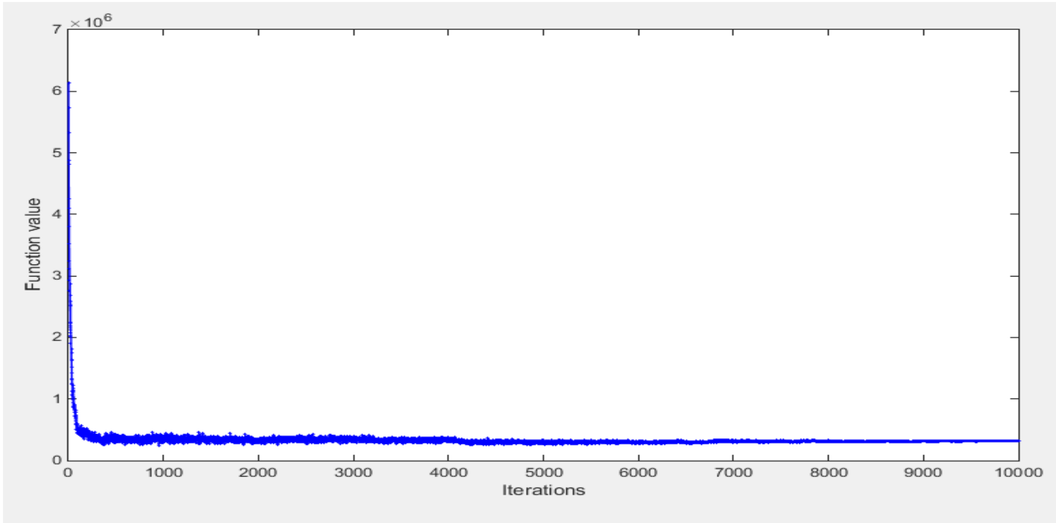

Figure 3-51: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 0.7, maximum service level 1, Random set#4)

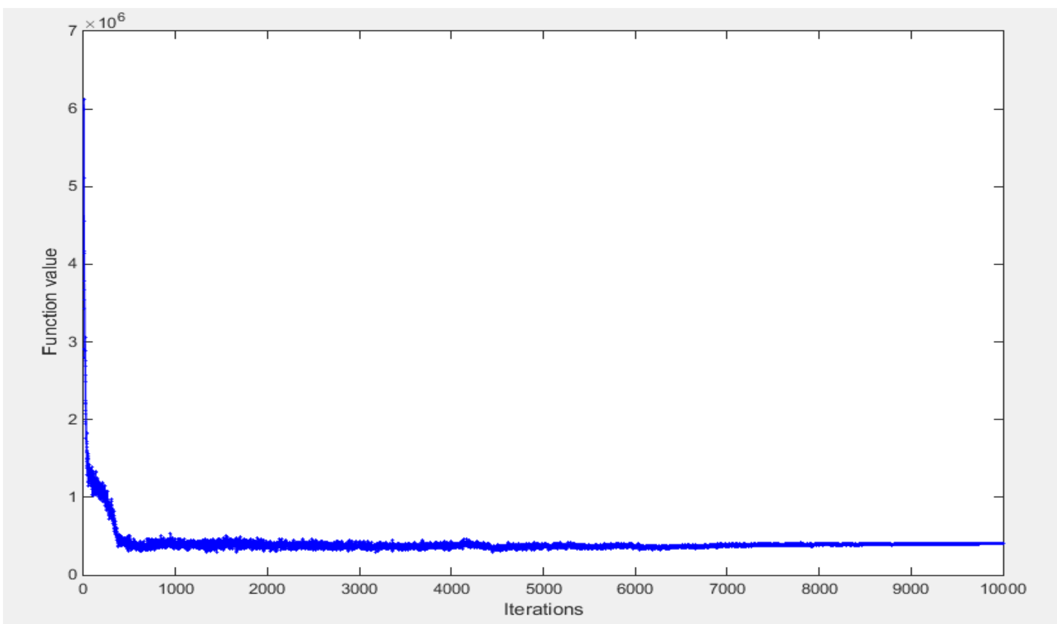

Figure 3-52: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 0.7, maximum service level 1, Random set#5)

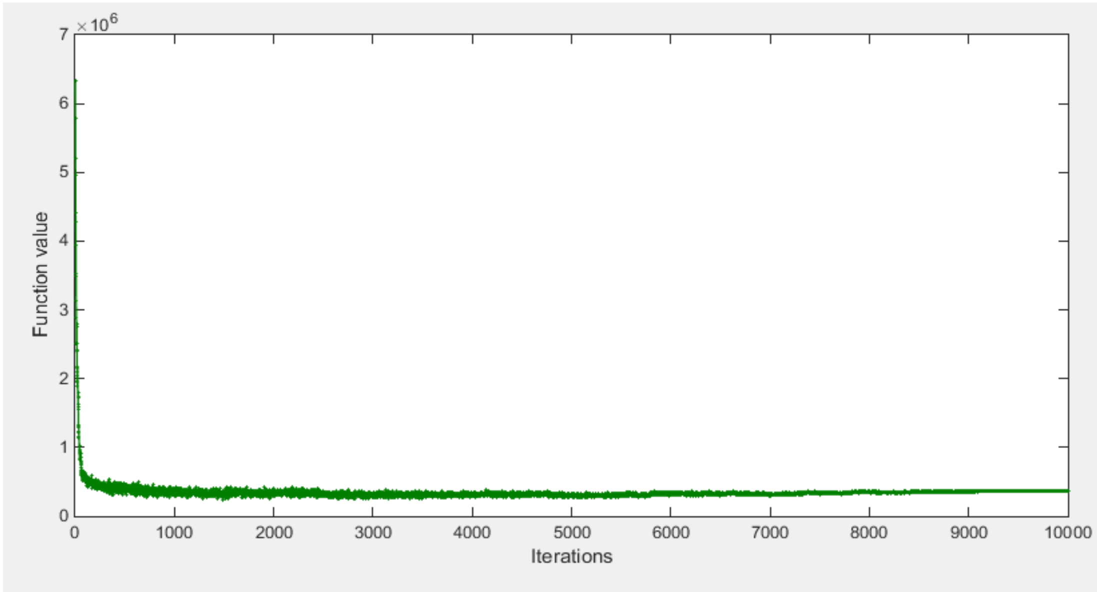

Figure 3-53: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 1, maximum service level 1, Random set#1)

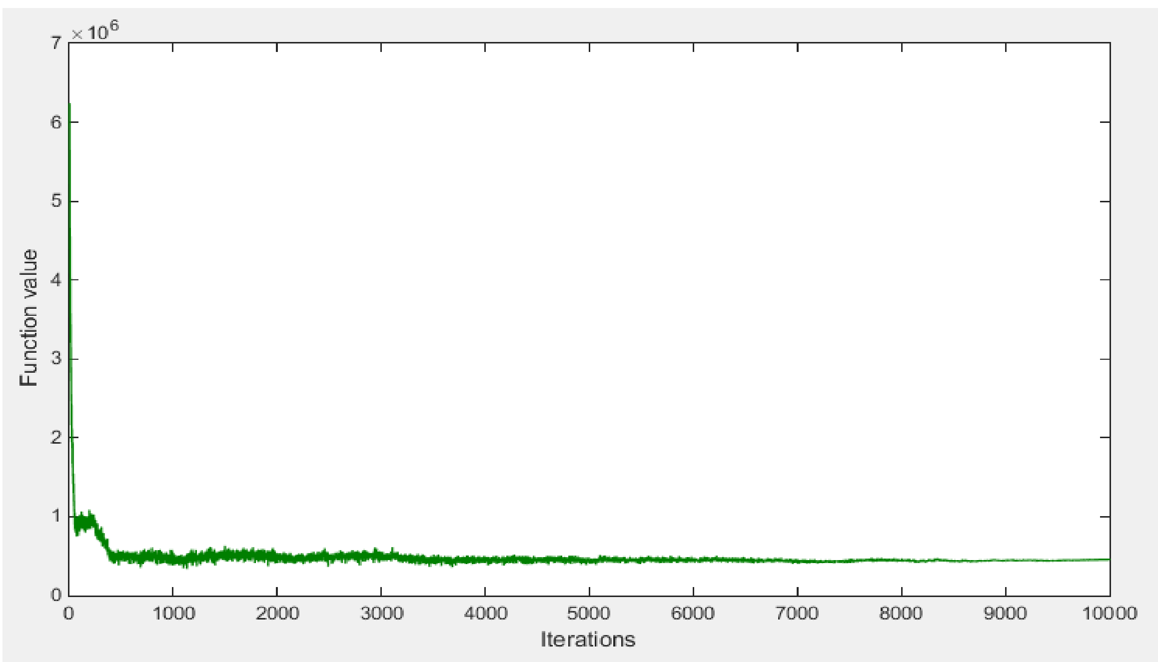

Figure 3-54: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 1, maximum service level 1, Random set#2)

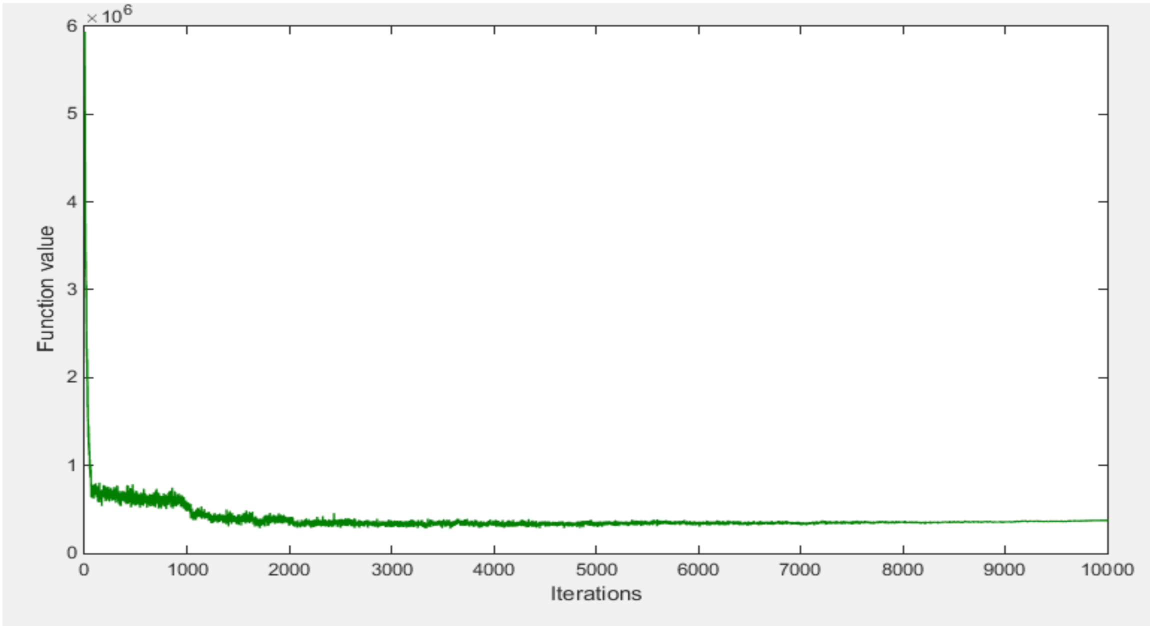

Figure 3-55: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 1, maximum service level 1, Random set#3)

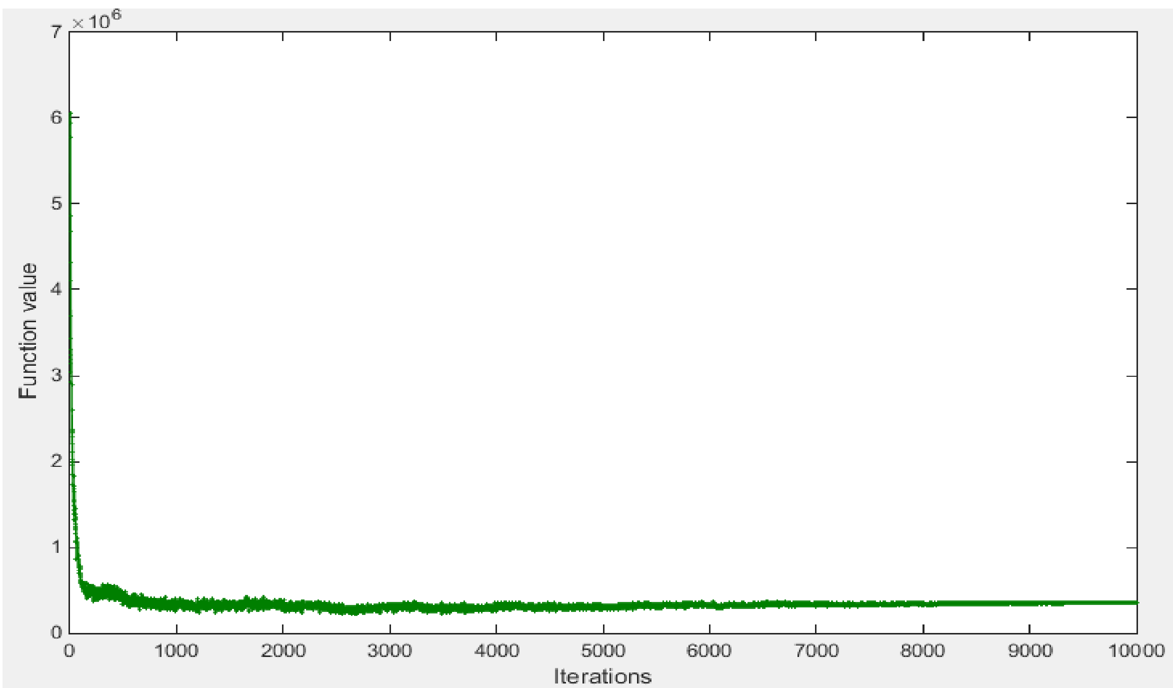

Figure 3-56: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 1, maximum service level 1, Random set#4)

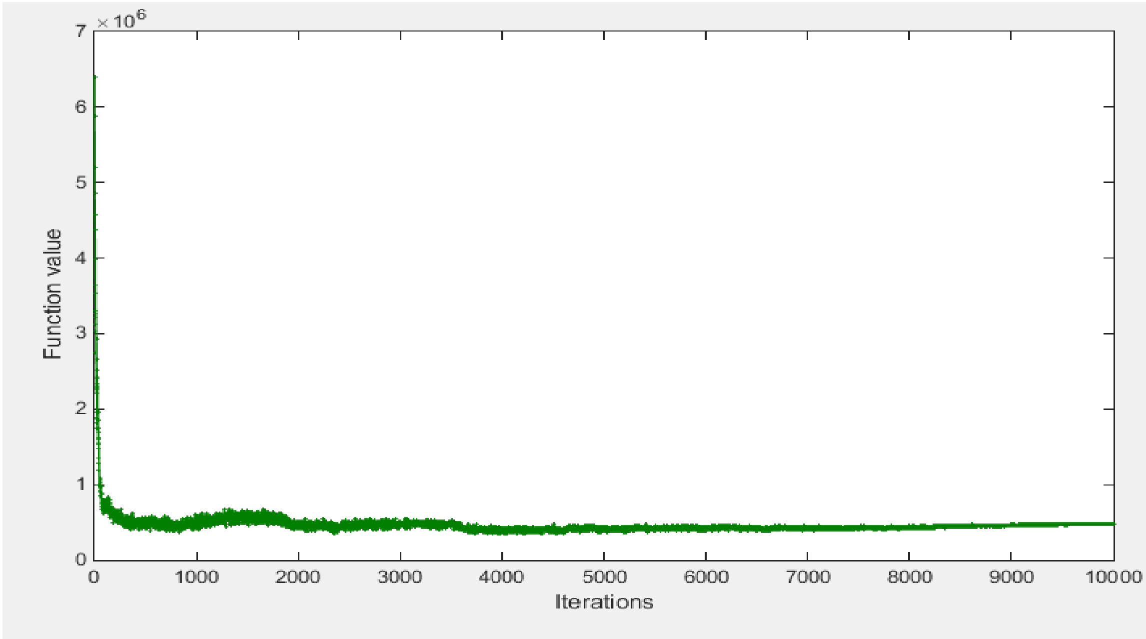

Figure 3-57: Achieved current function value for the best solution found by Grey Wolf Optimizer algorithm (minimum service level 1, maximum service level 1, Random set#5)

3.5 Summary

Due to the recently changed environmental requirements, proposing optimization models in order to make supply chain planning greener is essential. In this chapter, we presented a non-linear optimization approach that can be used for similar supply chains. It broadens new horizons for production managers and supply chain practitioners in order to consider sustainability issues in their planning decisions. Effective supply chain planning can be considered as a promising solution for greenhouse gas control in a whole supply chain. This research supports this statement by utilizing a case study and recommends various scenarios for supply chain practitioners based on trade-offs among service levels, CO_2 emissions, and the total costs of the supply chain network. The result verifies that the proposed nonlinear optimization model for the GSCP issue minimizes the carbon emissions and total costs of a given supply chain at a very acceptable and efficient level. This model can be utilized as an effective tool in the strategic planning for green supply chains.

Chapter 4

4 A new guideline for optimal performance evaluation of adaptive $\bar{X}$ control chart

A process that is stable and steady nonetheless, operating outside of desired and specified limits, needs to be improved through a measured effort to identify the causes and origins of current performance, and primarily, improve the process (Wheeler 2004). SPC refers to an industry-standard methodology that applies various statistical methods comprehensively to measure, control, and improve the quality of industrial processes, production systems, and service operations (Wheeler 2004). A control chart is one of the efficient tools of quality control in SPC and plays an important role in decreasing the amount of waste and defective produced products and components in manufacturing and production systems (Montgomery 1980). The first control chart was proposed by Shewhart (1931). The Shewhart $\bar{X}$ control chart is regularly utilized to detect large shifts in the mean of a process. The major limitation of this chart is its inadequate statistical efficiency towards the detection of small and moderate shifts in the mean of a process. As a traditional Shewhart control $\bar{X}$ chart with FP does not function fast enough to detect small to moderate shifts and variances of process parameters, new alternatives mainly known as adaptive $\bar{X}$ control charts are recommended to enhance the performance of control charts through varying one or more design parameters (Reynolds 1996; Costa 1999; Lin and Chou, 2005; De Magalhaes *et. al*, 2009; Costa and Machado, 2011; Mahadik, 2013a; Lee, 2013; Lim *et al.*, 2015, Elahi and Franchetti, 2015b).

Based on recently obtained data from a process, design parameters that can be varied in an adaptive $\bar{X}$ control chart include: the sample size, sampling interval, and width coefficient of control limits. Various studies have focused on the schemes of the VSS (Costa, 1994; Castagliola *et al.*, 2012), VSI (Reynolds, 1996; Chou *et al.*, 2006; Zhang *et al.*, 2012b; Yang and Yang 2013), and VSC (Chen *et al.*, 2008; Lee *et al.*, 2013). Some studies have also considered more than one variable design parameter such as VSSI (Costa 1997; Wu *et al*., 2007b; Jensen *et al*., 2008; Yang and Yang, 2013; Lim *et al.*, 2015), VSIC (Chen *et al.*, 2008; Mahadik 2013b), variable sample size and VSSC (Chen *et al.*, 2008; Mahadik, 2013a), and VP (Costa, 1999; Costa and Machado, 2011; Guo *et al*., 2014). These studies verify the efficiency of applied adaptive schemes in detecting small mean shifts sooner than FP control charts.

The study of recent literature in areas of adaptive $\bar{X}$ control charts reveals that various statistical performance measures are also defined and utilized to evaluate the performance and efficiency of these control charts containing: ANOS (Chen *et al*., 2008; Lee *et al*., 2012a; Mahadik, 2013a; Guo *et al*., 2014), ANSS (Castagliola *et al.*, 2012; Mahadik, 2013a; Mahadik, 2013b; Guo *et al*., 2014), ATS (Wu *et al*., 2007b; Jensen *et al*., 2008; Chen *et al*., 2008; Zhang *et al*., 2012a; Lee *et al*., 2012a; Lee *et al*., 2012b; Yang and Yang, 2013; Niaki and Jahani, 2013; Lim *et al*., 2015), AATS (De Magalhaes *et al.*, 2009; Costa and Machado, 2011; Lee *et al*., 2012a; Guo *et al.*, 2014), MATS (Wu *et al.*, 2007b), steady-state average time to signal (SSATS) (Mahadik, 2013a), ANSW

(Chen et al., 2008), ASWR (Chen *et al*., 2008), AEQL (Lim *et al*., 2015), SDTS (Jensen *et al*., 2008; Zhang *et al.*, 2012a; Lim *et al.*, 2015), ARL (Lee et al., 2012b; Niaki and Jahani, 2013), and SDRL (Castagliola *et al.*, 2012). Moreover, recently a number of new trends and developments have been applied to the study of control charts such as the application of adaptive $\bar{X}$ control charts for correlated data (Chen *et al*., 2007), the use of multivariate control charts for monitoring the process mean vector when quality characteristics of interest are multivariate (Reynolds and Stoumbos 2008; Wang 2012; Niaki and Jahani 2013), the utilization of evolutionary algorithms (i.e. genetic algorithm and particle swarm algorithm) and Mont-Carlo simulation for finding the optimal chart parameters (Wang 2012; Lee *et al.*, 2012b; Niaki and Jahani, 2013; Ahmed *et al.*, 2014; Morabi *et al.*, 2015), the use of double sampling for increasing the efficiency of adaptive $\bar{X}$ control charts (Costa and Machado, 2011; Lee *et al.*, 2012a; Lee *et al.*, 2012b; Lee 2013), the application of time-weighted adaptive control charts for displaying the cumulative sums of the deviations of each sample value from the target value (Ou *et al.*, 2012; He *et al.*, 2014), and the employment of adaptive $\bar{X}$ control charts for case studies with estimated design parameters (Zhang *et al*., 2012a; Castagliola *et al.*, 2012; Lim *et al.*, 2015).

Practically, it is essential for process engineers and decision makers know how to set the initial parameters of the utilized control chart to detect the specified shift size as soon as possible. In reality, decision makers do not have enough information about the instant the process changes or the magnitude of the change. However, they can predict and define how much the studied production system is sensitive with respect to various ranges of shifts in mean, based on their recognition toward a production system, product type, and defined objectives. For instance, decision makers and quality managers can be more sensitive toward small ranges of shifts in mean when they conduct quality control in medical industries, health care production systems, and clinical laboratories (Helms 2009). Although the properties of the adaptive $\bar{X}$ control charts have been exhaustively studied in previous research papers (Costa, 1999; De Magalhaes *et al.*, 2009; Mahadik, 2013a, b), to the best of our knowledge, no study has been done to find optimal points of the response surface in the context of performance evaluation of adaptive $\bar{X}$ control charts, which is the overall goal of this study. In this research, we apply a reverse approach and focus on revealing more information about optimal points of the response surface in which the defined performance measures of adaptive $\bar{X}$ control charts have their minimum values. In other words, unlike previous conducted research works that considered definite values for design parameters and compared the performance of all adaptive $\bar{X}$ control charts just for a specific set of design parameters using a forward approach (e.g. Costa, 1999; De Magalhaes *et al*., 2009), here we utilize a backward perspective to find various sets of design parameters in the response surface, with respect to each adaptive $\bar{X}$ control chart and broad ranges of shifts in mean, where each of defined performance measures hold their optimal minimum value. Through this reverse perspective, decision makers and quality managers will have access to new statistical guideline tables and diagrams with more information about design parameters in optimal points of each adaptive $\bar{X}$ control chart, values of defined performance measures at these points, and improvement percentages in comparison to the FP control chart for various ranges of shifts in mean. Using these statistical guideline tables and diagrams will help decision makers have a broader overlook toward optimal points before choosing a proper adaptive $\bar{X}$ control chart, appropriate performance measures, and cost-effective design parameters to detect preferred ranges of shifts in mean and monitor the process efficiently. For this purpose, we initially search the entire feasible response space by considering coded loops on all possible sets of design parameters derived from literature to find optimal minimum values of each of defined performance measures containing AATS, ANOS, and ANSS. Secondly, the defined algorithm stores the achieved sets of design parameters for each obtained optimal minimum value of a specific performance measure and computes the value of other performance measures and all of the related design parameters considering broad ranges of shifts in mean (small, medium, and large shifts). Thirdly, the improvement percentages of performance measures in comparison to the FP $\bar{X}$ control chart are computed and all obtained information is recorded in tables and diagrams. In this way, new statistical guideline tables for decision makers are presented which reveal more information about optimal points of each adaptive $\bar{X}$ control chart for various ranges of shifts in mean. Utilizing the presented tables as an efficient guideline and the outcome of this research paper enables decision makers and quality managers to a) choose a proper adaptive $\bar{X}$ control chart based on their preferred level of complexity in model design, b) select an appropriate performance measure/measures which is/are economically viable in terms of sampling expense, and c) set right initial design parameters based on a trade-off between improvement percentage and potential costs of sampling. The rest of this chapter is structured as follows. Section 4-1 and its sub-sections focus on the applied methodology. In Section 4-2 the obtained results are illustrated and discussed. Finally, the summary is presented in Section 4-3.

4.1 Methodology

4.1.1 Adaptive $\bar{X}$ Control Charts and Performance Measures

In this study, seven different adaptive $\bar{X}$ control charts and a fixed parameters (FP) $\bar{X}$ control chart are considered in our evaluation as follows:

1. VIS model with two different sampling intervals (h_1, h_2 where $h_1 > h_2$) (Figure 4-1)
2. VSS model with two different sampling sizes (n_1, n_2 where $n_1 < n_2$) (Figure 4-2)
3. VSC model with two different width coefficients of control limits (K_1, K_2 where $K_2 < K_1$) (Figure 4-3)
4. VSSI model with two different sample sizes (n_1, n_2 where $n_1 < n_2$) and two different sampling intervals (h_1, h_2 where $h_1 > h_2$) (Figure 4-4)
5. VSIC model with two different sampling intervals (h_1, h_2 where $h_1 > h_2$) , two different width coefficients of control limits (K_1, K_2 where $K_2 < K_1$), and two different threshold limits (W_1, W_2 where $W_2 < W_1$) (Figure 4-5)
6. VSSC model with two different sample sizes (n_1, n_2 where $n_1 < n_2$), two different width coefficients of control limits (K_1, K_2 where $K_2 < K_1$), and two different threshold limits (W_1, W_2 where $W_2 < W_1$) (Figure 4-6)
7. VP model with two different sample sizes (n_1, n_2 where $n_1 < n_2$), two different sampling intervals (h_1, h_2 where $h_1 > h_2$), two different width

coefficients of control limits (K_1, K_2 where $K_2 < K_1$), and two different threshold limits (W_1, W_2 where $W_2 < W_1$) (Figure 4-7)

8. FP $\bar{X}$ control chart with fixed design parameters ($n_0, h_0,$ and K_0 respectively represent the sample size, the sampling interval, and the width coefficient of the control limits) (Figure 4-8)

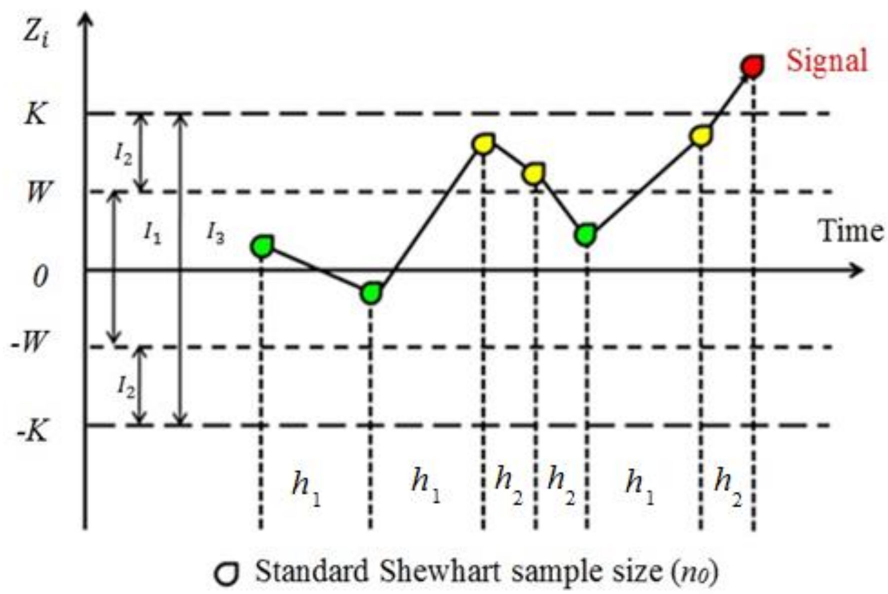

Figure 4-1: VSI control chart

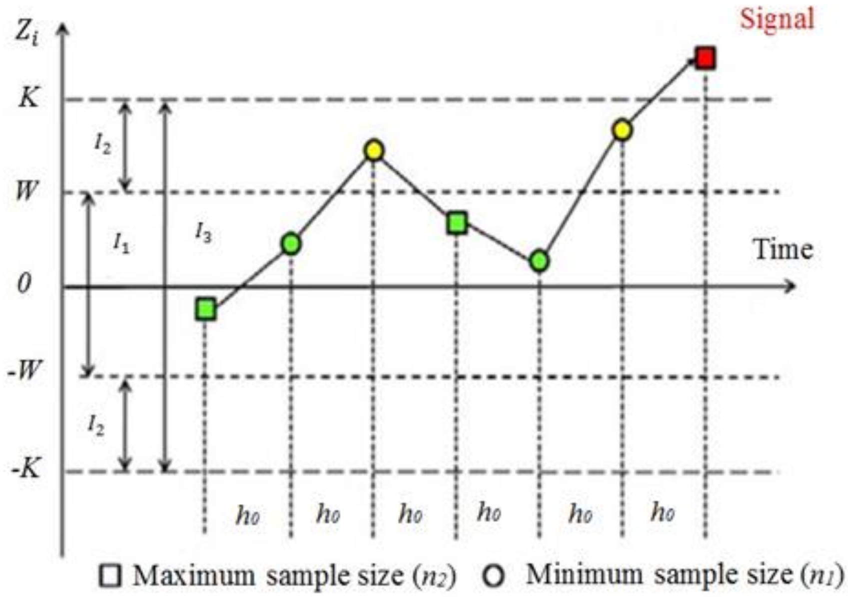

Figure 4-2: VSS control chart

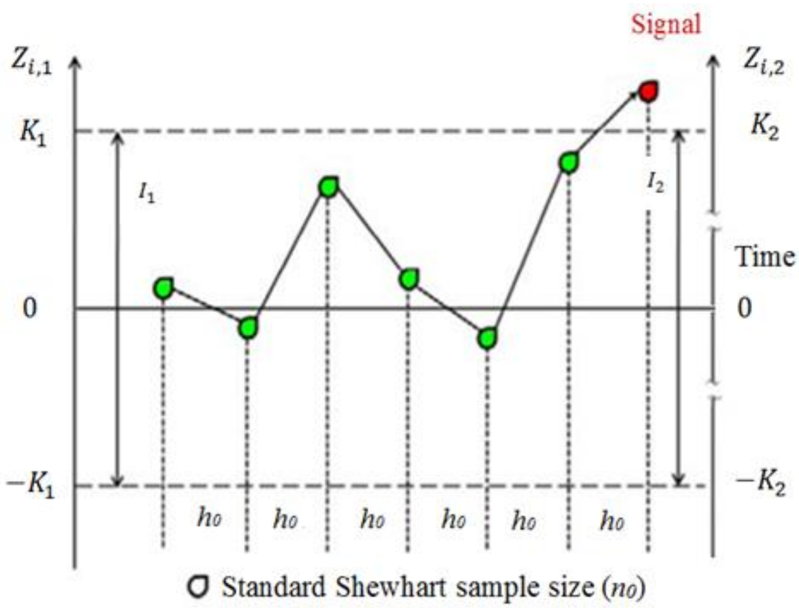

Figure 4-3: VSC control chart

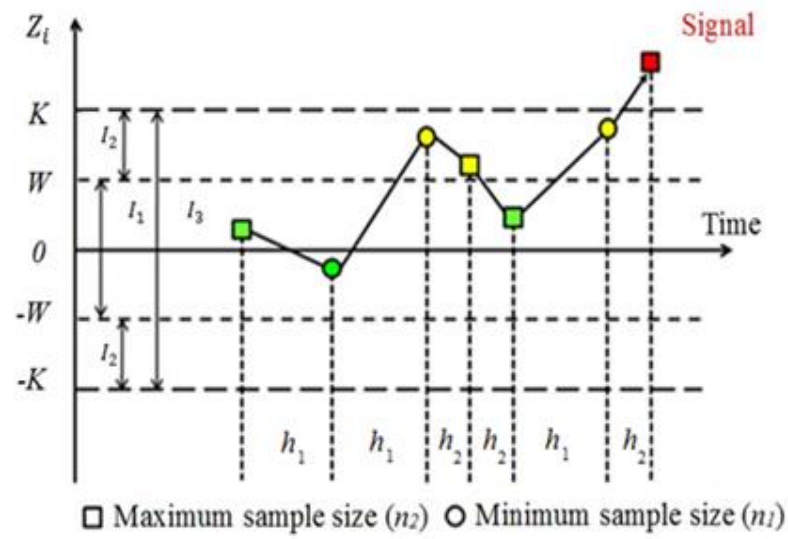

Figure 4-4: VSSI control chart

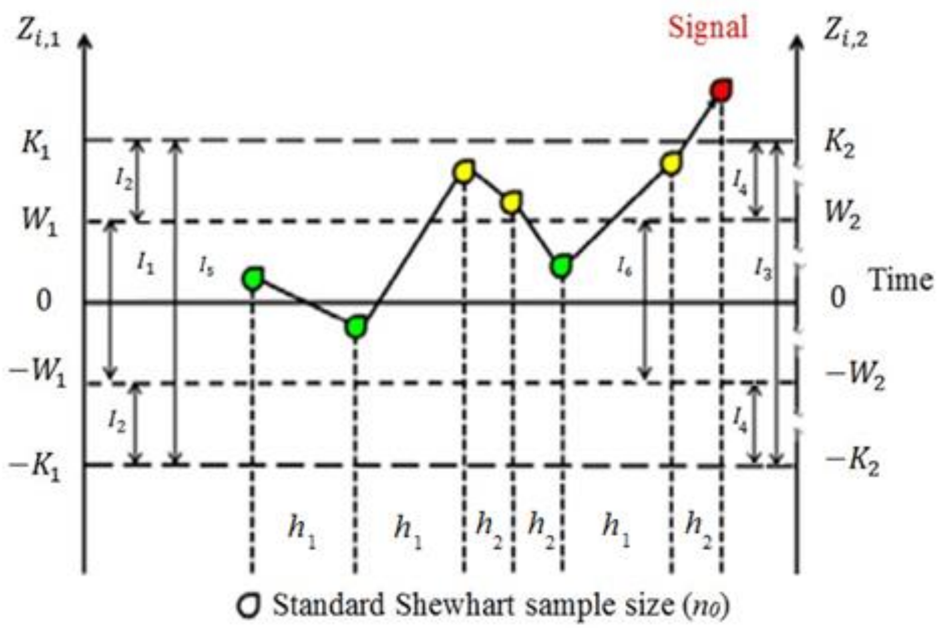

Figure 4-5: VSIC control chart

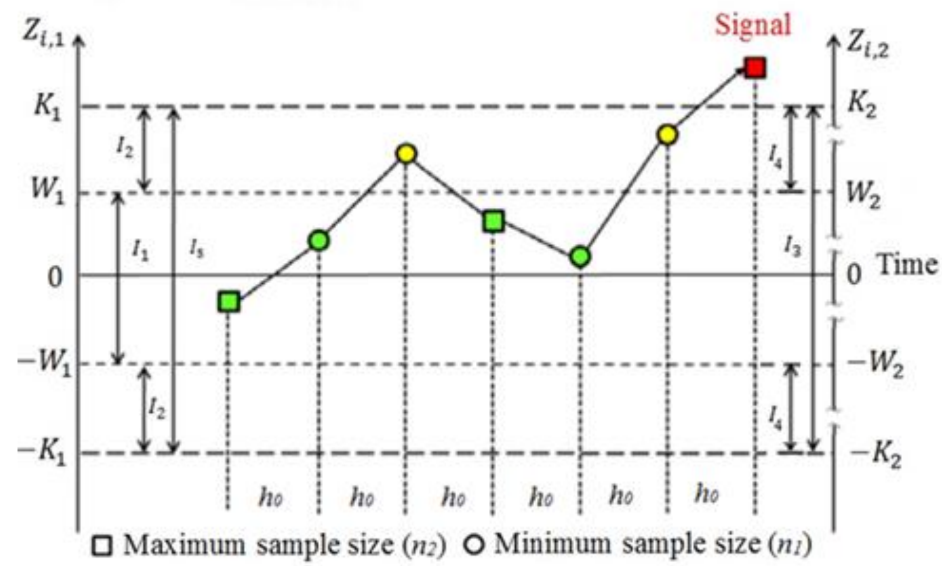

Figure 4-6: VSSC control chart

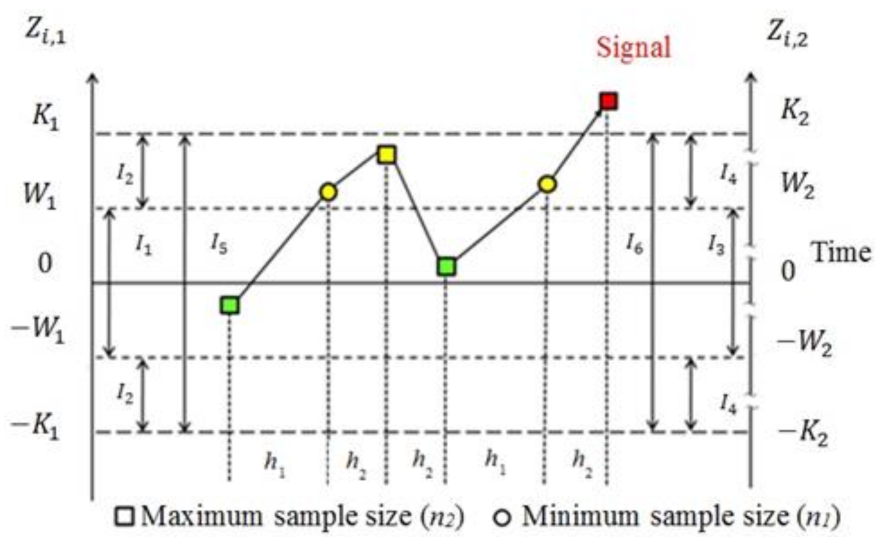

Figure 4-7: VP control chart

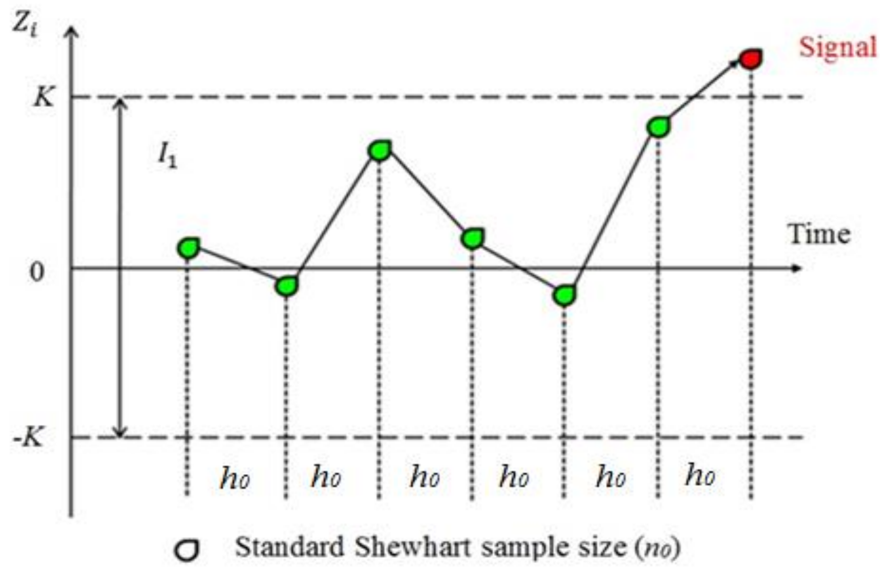

Figure 4-8. Standard Shewhart control chart

We also take three statistical measures of efficiency for the eight control charts into account: ANOS, ANSS, and AATS. ANOS is the expected value of the number of inspected items from the start of the process until the chart signals (Chen *et al.*, 2008). ANSS is the expected value of the number of samples taken from a shift to the time the chart signals (Mahadik, 2013b). And AATS represents the average time since t the mean of a process is off-target till the control chart alarms (De Magalhaes *et. al*, 2009; Zhang *et al.*, 2012b).

Here, we have assumed that the process starts in statistical control and then it moves to an out-of-control status in future. The shift occurrence time is also an exponentially distributed random variable. In evaluating the performance of control charts, it is needed to compare their performances under equal conditions. For this purpose, the in-control performance of the seven adaptive control charts and the FP control chart are aligned with each other. The applied statistical design model is described in the following section.

4.1.2 Applied Statistical Design Model

A statistical design model similar to the model presented by De Magalhaes *et. al* (2009) is applied. They focused on a specific set of design parameters subjected to a surveillance policy (De Magalhaes *et. al*, 2009). However, here we search the entire response space to disclose more information such as design parameters and improvement percentages about optimal points in which performance measures hold their minimum values. Here, it is assumed that the quality characteristic of a process (X), that is being monitored by $\bar{X}$ control charts, follows a normal distribution with mean μ and a constant and known standard deviation σ. When the mean of a quality characteristic is at its target value of the process mean μ_0, the process considered as in-control and when μ changes from μ_0 to $\mu_1 = \mu_0 \pm \delta\sigma,\ \delta > 0$ it refers to an out-of-control process. Here, δ refers to the shift in the process mean and is expressed in process standard deviation units. When the process shifts to an out-of-control status, it remains in this state until the control chart gives a signal. Then a searching process starts to find and eliminate the related cause, choose the best statistical design for the next sampling, and set new values for design parameters. Let Z_i , $i = 1,2, \ldots$ refers to the value of standardized $\bar{X}_i$ which is calculated as follows (Jensen *et al.*, 2008; Mahadik, 2013b):

$$Z_i = \frac{\bar{X}_i - \mu_0}{\frac{\sigma}{\sqrt{n_i}}}$$

Equation 4.1.2-1

Where $\bar{X}_i, i = 1,2, \ldots$ is the i^{th} subgroup computed mean using n_i and t_i which refer to sample size and sampling interval successively (for $\mu = \mu_0, Z_i \sim N(0,1)$).

We assume when the process is in-control status (state A where $X \sim N(\mu_0, \sigma_0^2)$) in each moment of sampling it is possible to have one of these scenarios: LC^A :loose control, mean: on target, SC^A :strict control, mean: on target, or FA: false alarm. Loose control stands for controlling a process when the current sample statistic plotted on the control chart is close to the center line, therefore, the next sample is taken from the process with a smaller sample size and/or a longer sampling interval and/or a larger control limit coefficient. In contrast, strict control chart refers to controlling a process once the current sample statistic is plotted close to the control limits (but still within them), hence, the next sample is taken from the process with a larger sample size and/or a shorter sampling interval and/or a smaller width coefficient of control limits in order to detect the possible shift as soon as possible.

The size of the first sampling of the process while it is just started (or re-starting after an assignable cause explore and remediation, when appropriate) is randomly selected with a probability p_0 of starting in a state of loose control. Alongside the in-control duration, all samples, including the first one, should have a probability p_0 under loose control and a probability $(1 - p_0)$ under strict control (Equation 4.1.2-2).

$$p_0 = \begin{cases} P(|Z| < W_1 \; given \; that \; |Z| < K_1) \\ P(|Z| < W_2 \; given \; that \; |Z| < K_2) \end{cases} \quad ; \text{Where } Z \sim N(0,1)$$

Equation 4.1.2-2

LC^A and SC^A are considered as transient states, whereas FA is an absorbing state. The transition matrix of these three states and the transition matrix between the two transient states are shown in Appendix A (Section A.1). The elements of these matrices represent the probability of a transition from a previous state to the current state, while the process is in-control status and the mean is on target.

When the process is out-of-control (state B: $X \sim N(\mu_0 \pm \delta\sigma_0, \sigma_0^2)$), it is possible to have one of these scenarios within the sampling process: LC^B (Loose control, mean: out of target), SC^B (Strict control, mean: out of target), and TA (true alarm and signal). The transition matrix of these three states and the transition matrix between the two transient states are demonstrated in Appendix A (Section A.2). The elements of these matrices signify the probability of a transition from a previous state to the current one, while the process is out-of-control and the mean is off target.

The aforementioned matrices are utilized to formulate the considered three performance measures: AATS, ANOS, and ANSS. These formulations are displayed in Appendix A (Section A.3) and are applied for coding performance measures in the proposed algorithm by the following section.

4.1.3 The proposed algorithm for finding optimal points

Unlike previous researches (e.g. Costa, 1999; De Magalhaes *et al.*, 2009; Mahadik, 2013a) which applied a forward viewpoint and focused on just a specific set of design parameters to compare performance of various models, here we use a reverse approach to search the entire response space in order to disclose more information about the optimal points located in the response space in which performance measures have their minimum values. For this purpose, we attempt to find three optimal points for each of the seven adaptive models in regard to AATS, ANOS, and ANSS with considering a broad range of shift in mean (small, medium, and large shifts). Then, we obtain the initial design parameters at these optimal points and records them. At each achieved optimal point which is related to the minimization of one the performance measures' value, we get the values of the two other performance measures and record their related initial design parameters, too. After getting this information for the seven adaptive models, we compute the improvement percentages of performance measures in comparison to the FP control chart. We conduct such an analysis for various ranges of shifts in mean at the achieved optimal points of the response surface. To search the entire response surface for broad ranges of shifts in mean, coded loops using a MATLAB (R2015a) computer programming on possible sets of design parameters, extracted from literature (Table 4.1.3.1), are utilized.

Table 4.1.3.1: The range and variation step for the adaptive $\bar{X}$ control chart design parameters

Variable	Minimum Value	Maximum Value	Step
h_1	$h_0 + 0.01$	3	0.01
h_2	0.01	$h_0 - 0.01$	0.01
n_1	1	$n_0 - 1$	1
n_2	$n_0 + 1$	30	1
W_1	0.1	$K_1 - 0.1$	0.1
W_2	0.1	$K_2 - 0.1$	0.1
K_1	0.2	2.9	0.1
K_2	3.1	6	0.1

FP parameters: $n_0 = 5$, $h_0 = 1$, $K_0 = 3$

$\lambda = 0.0001$

$\delta \in \{0.25, 0.5, 0.75, 1.00, 1.25, 1.50, 2.00, 2.50, 3.00\}$

The evolutionary or meta-heuristic algorithms like genetic algorithm can be used for this purpose, but they might mistakenly use a local optimum instead of a global one and does not result in an exact response. Since the considered search method goes through the entire space, the pitfall of local optimal is avoided. The proposed procedure has the following steps:

Step1. Initially, the coded algorithm forms for-loops on all possible combinations of h_1, h_2, n_1, n_2, W_1, W_2, K_1, K_2 and fixes $n_0 = 5$, $h_0 = 1$, and $K_0 = 3$ as the FP parameters. The range and variation step of these parameters are shown in Table 4.1.3.1.

Step2. The algorithm specifies various δ values (small, medium, and large shifts in mean) and searches to find the minimum AATS value for each of predetermined shifts in mean of δ with respect to the VP model. AATS formulation is demonstrated in Equation A.3-5 of the supplementary materials.

Step3. The algorithm stores the specific combination of design parameters related to the obtained optimal minimum AATS value for each of specific shift sizes.

Step4. The algorithm computes the value of other performance measures (here, ANOS and ANSS) at the achieved optimal points for the AATS measure (using Equation A.3-6 and A.3-7 of the supplementary materials).

Step5. The algorithm computes the improvement percentage (% IM) of obtained values for each performance measure (PM) of the AATS, ANOS, and ANSS in comparison to the FP control chart for various ranges of shifts in mean (using Equation 4.1.3-3). The FP chart is applied as a reference of comparisons (Table 4.1.3.2). Data demonstrated in Table 4.1.3.2 as a reference is obtained based on fixing the FP parameters and using PM's formulations. This data matches with presented standard numbers in previous studies in the literature (De Magalhaes *et al.*, 2009; Cheng *et al.*, 2013)

$$\% \, IM_{PM} = \frac{PM_{FP\ control\ chart} - PM_{adaptive\ control\ chart}}{PM_{FP\ control\ chart}}$$

Equation 4.1.3-3

Table 4.1.3. 2: The optimum value of the AATS, ANOS, and ANSS in various shifts in mean for the FP control chart

δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
AATS	133.15940	33.40080	10.76110	4.49530	2.38770	1.56650	1.07580	1.00480	1.00010
ANOS	665.79720	167.00390	53.80530	22.47660	11.93830	7.83250	5.37920	5.02410	5.00050
ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010

$\% \, IM_{PM}$ refers to the improvement percentage of a performance measure for a given adaptive control chart. The term of $PM_{FP\ control\ chart}$ is the value of a given performance measure for the FP control chart. The term of $PM_{adaptive\ control\ chart}$ is the value of the same performance measure for the given adaptive control chart.

Step6. The algorithm follows a similar procedure using steps 2-5 to find the minimum ANOS and ANSS values for each of predetermined shifts in mean of δ with respect to the VP model.

Step7. The algorithm repeats the steps of 2-6 to find the minimum AATS, ANOS, and ANSS values for each of predetermined shifts in mean of δ with respect to the rest of models including VSC, VSI, VSIC, VSS, VSSC, and VSSI.

4.2 Results and Discussion

Based on the proposed algorithm for finding the optimal points of the various models that was described earlier, the obtained results for minimum values of AATS, ANOS, and ANSS with respect to various ranges (small: $\delta \, \epsilon\{0.25, 0.50, 0.75\}$, medium: $\delta \, \epsilon\{1.00, 1.25, 1.50\}$, and relatively large: $\delta \, \epsilon\{2.00, 2.50, 3.00\}$) of shifts in mean for the VP model is presented in Tables 4.2.1. Similarly, the achieved results for optimal minimum values of performance measures for the rest of adaptive models entailing VSC, VSI, VSIC, VSS, VSSC, and VSSI are demonstrated in Tables A.4.1 to A.4.6 of the Supplementary Materials (Appendix A.4). These tables provide decision makers with efficient information by showing the sets of design parameters in which minimum value for each of the performance measures in various adaptive control charts occur with respect to broad ranges of shifts in mean (small, medium, and relatively large). They also offer more information about the value of other performance measures and improvement percentages in comparison to the FP control chart at these obtained optimum discrete points located in the whole feasible response space. In this way, decision makers and quality managers can apply the presented data as an efficient guideline to select the most effective adaptive $\bar{X}$ control chart, performance measures, and design parameters with respect to a range/ranges of shifts in mean that is/are more significant in their process.

Table 4.2.1: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VP model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VP** Model	Optimum AATS	31.11548	6.12724	2.68081	1.79718	1.56932	1.51749	1.50153	1.50017	1.50002
	% IM	76.63	81.66	75.09	60.02	34.27	3.13	-39.57	-49.30	-49.99
	ANOS	205.64350	54.39360	29.29199	17.55353	11.29634	7.97352	5.63964	5.08826	5.00871
	% IM	69.11	67.43	45.56	21.90	5.38	-1.80	-4.84	-1.28	-0.16
	ANSS	32.35305	6.93023	4.01036	2.87372	2.05927	1.49769	1.10668	1.01471	1.00124
	% IM	75.70	79.25	62.73	36.07	13.75	4.39	-2.87	-0.98	-0.11
	h_1	1.16	1.26	1.59	1.99	2.98	1.99	1.99	1.99	1.50
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	2	3	3	4	4	4	4
	n_2	30	20	10	7	6	6	6	6	7
	W_1	1.48	1.25	0.89	0.67	0.43	0.67	0.67	0.67	0.96
	W_2	1.42	1.22	0.88	0.67	0.43	0.67	0.67	0.67	0.96
	K_1	6.00	6.00	5.00	3.80	3.40	3.10	3.10	3.10	3.10
	K_2	2.33	2.49	2.69	2.79	2.90	2.92	2.92	2.92	2.86
Minimizing **ANOS** for the **VP** Model	AATS	31.11548	6.57984	3.12352	2.12544	1.70754	1.51749	1.50153	1.50017	1.50003
	% IM	76.63	80.30	70.97	52.72	28.49	3.13	-39.57	-49.30	-49.99
	Optimum ANOS	205.64350	50.91952	26.00355	15.99908	10.88660	7.97352	5.63964	5.08826	5.00561
	% IM	69.11	69.51	51.67	28.82	8.81	-1.80	-4.84	-1.28	-0.10
	ANSS	32.35305	6.80667	3.47683	2.40866	1.89824	1.49769	1.10668	1.01471	1.00094
	% IM	75.70	79.62	67.69	46.42	20.50	4.39	-2.87	-0.98	-0.08
	h_1	1.16	1.17	1.40	1.79	2.98	1.99	1.99	1.99	1.99
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	1	1	1	4	4	4	4
	n_2	30	28	15	10	7	6	6	6	6
	W_1	1.48	1.45	1.07	0.76	0.43	0.67	0.67	0.67	0.67
	W_2	1.42	1.39	1.05	0.76	0.43	0.67	0.67	0.67	0.67
	K_1	6.00	6.00	5.80	4.90	4.40	3.10	3.10	3.10	3.10
	K_2	2.33	2.36	2.60	2.74	2.87	2.92	2.92	2.92	2.92
Minimizing **ANSS** for the **VP** Model	AATS	31.11548	6.27686	2.94378	2.00680	1.66237	1.53827	1.50153	1.50017	1.50003
	% IM	76.63	81.21	72.64	55.36	30.38	1.80	-39.57	-49.30	-49.99
	ANOS	205.64350	51.65814	26.89955	17.89733	12.11030	8.66797	5.63964	5.08826	5.00561
	% IM	69.11	69.07	50.01	20.37	-1.44	-10.67	-4.84	-1.28	-0.10
	Optimum ANSS	32.35305	6.71823	3.35499	2.29905	1.78905	1.47120	1.10668	1.01471	1.00094
	% IM	75.70	79.89	68.82	48.86	25.07	6.08	-2.87	-0.98	-0.08
	h_1	1.16	1.21	1.27	1.25	1.20	1.33	1.99	1.99	1.99
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	2	3	4	4	4	4	4
	n_2	30	24	16	13	10	8	6	6	6
	W_1	1.48	1.36	1.24	1.28	1.38	1.15	0.67	0.67	0.67
	W_2	1.42	1.32	1.22	1.26	1.37	1.14	0.67	0.67	0.67
	K_1	6.00	6.00	4.30	3.30	3.10	3.10	3.10	3.10	3.10
	K_2	2.33	2.42	2.50	2.59	2.72	2.81	2.92	2.92	2.92

Analyzing the results also indicate on obtaining some identical optimal points while minimizing performance measures for each of adaptive models with respect to various ranges of shifts in mean (small, medium, or relatively large). From a statistical viewpoint, it can refer to this fact that for some specific shifts in mean of various adaptive models, optimal minimum values of two or three considered performance measures and their related design parameters converge to the same point. Statistical definitions of the AATS, ANOS, and ANSS signify when a process works in an out-of-control condition, a scheme which has a shorter AATS, smaller ANSS, and smaller ANOS is more desirable as such a control chart can detect an off-target condition faster with fewer inspected items. Such a condition results in less sampling costs and less effort and we can avoid producing a lot of nonconforming items. Considering these facts, once identical optimal points with an acceptable improvement percentage in terms of performance are obtained for specific ranges of shift in mean with respect to an adaptive model, it verifies that performance measures function equally at those optimal points from a statistical perspective. Therefore, in such cases decision makers and quality managers can consider their economical viewpoint and choose the best performance measure among the statically equivalent performance measures if they prefer to focus on controlling the quality of their process for a given specific range of shift in mean.

As an example, based on the presented results for the VP model in Table 4.2.1, the same optimal points with acceptable improvement percentages are obtained while minimizing AATS, ANOS, and ANSS for a small shift in mean of $\delta = 0.25$. Identical optimal points are also achieved when minimizing AATS and ANOS for a medium shift mean of $\delta = 1.50$ but the improvement percentage of ANOS is less than zero at these points. Therefore, from a statistical viewpoint in such a case, choosing AATS is better than selecting ANOS. The same optimal points with negative improvement percentages are also obtained while minimizing AATS, ANOS, ANSS for relatively large shifts in mean of $\delta \epsilon\{2.00,2.5\}$. Moreover, the identical optimal points with negative improvement percentages are obtained once minimizing ANOS and ANSS for a relatively large shift mean of $\delta = 3$. Thus, statistically choosing VP model is not a proper decision for controlling the process quality for relatively large shifts in mean.

The obtained results shown in Table A.4.1 signify that for the VSC model, same optimal points with negative or close to zero values for improvement percentages are obtained while minimizing AATS, ANOS, and ANSS for all considered ranges of shifts in mean. Thus, from statistical viewpoint, the functionality's rank of the VSC model places near/ after the FP control chart and after the other adaptive models for small and medium shifts in mean. In terms of relatively large shifts in mean, its rank places near or after the FP control chart.

The achieved results demonstrated in Table A.4.2 denote that for the VSI model, identical optimal points with acceptable improvement percentages are obtained while minimizing ANOS and ANSS for small and medium shifts in mean of $\delta \epsilon\{0.25, 0.50, 0.75, 1.00,1.25\}$.

Table A.4.3 shows that for the VSIC model, same optimal points are obtained when minimizing ANOS and ANSS for all considered ranges of shifts in mean. Among them for the small and medium shifts in mean of $\delta \epsilon\{0.25, 0.50, 0.75, 1.00,1.25\}$, the computed improvement percentages are positive whereas for the relatively large shifts in mean of $\delta \epsilon\{1.5, 2.00,2.5,3.00\}$ the improvement percentages are equal to zero or negative values.

Table A.4.4 demonstrates that for the VSS model, same optimal points with positive improvement percentages are found while minimizing AATS, ANOS, and ANSS for small shifts in mean of $\delta \epsilon\{0.25, 0.50\}$. Based on this table, identical optimal points with acceptable improvement percentages are obtained while minimizing AATS and ANOS for small and medium shifts in mean of $\delta \epsilon\{0.75, 1.00\}$. Furthermore, the same optimal points with negative improvement percentages are obtained while minimizing all performance measures for relatively large shifts in mean of $\delta \epsilon\{2.00, 2.50,3.00\}$. Therefore, statistically choosing VSS model is not a proper decision for controlling the process quality for relatively large shifts in mean.

Table A.4.5 verifies that for the VSSC model, the same optimal points with positive improvement percentages are obtained while minimizing AATS, ANOS, and ANSS for a small shift in mean of $\delta = 0.25$. It also shows that identical optimal points with positive improvement percentages are obtained once minimizing AATS and ANSS for small and medium shifts in mean of $\delta \epsilon\{0.50, 0.75, 1.00\}$. This table also displays that the same optimums with negative improvement percentage for the ANOS measure are found when minimizing AATS and ANSS for a medium shift in mean of $\delta = 1.25$. It also verifies that identical optimums with negative improvement percentages for the AATS and ANOS measures are found when minimizing AATS and ANSS for a relatively large shift in mean of $\delta = 1.50$. Additionally, based on this table for the VSSC model, the similar optimal points with negative improvement percentages are achieved while minimizing all performance measures for relatively large shifts in mean of $\delta \epsilon\{2.00, 2.5, 3.00\}$.

Table A.4.6 demonstrates that for the VSSI model, same optimal points with positive improvement percentages are obtained while minimizing AATS, ANOS, and ANSS for a small shift in mean of $\delta = 0.25$. It also verifies that identical optimums with positive improvement percentages are achieved once minimizing ANOS and ANSS for a small shift in mean of $\delta = 0.50$. It also shows that the same optimums with negative improvement percentage for the ANOS measure are obtained once minimizing AATS and ANOS for a medium shift in mean of $\delta = 1.50$. On the basis of data presented by this table, the similar optimal points with negative improvement percentages are achieved while minimizing all performance measures for relatively large shifts in mean of $\delta \epsilon\{2.00, 2.5, 3.00\}$.

In accordance with obtained results in the aforementioned tables, the optimum values of AATS for all adaptive control charts and the FP chart have depicted with respect to various ranges of shift in mean: small shifts of $\delta \epsilon \{0.25,0.50,0.75\}$, medium shifts of $\delta \epsilon\{1.00,1.25,1.50\}$, and relatively large shifts of $\delta \epsilon \{2.00,2.50, 3.00\}$ through Figure 4-9. The optimum value of ANOS and ANSS for all adaptive control charts and the FP chart are also shown through Figure 4-10 and Figure 4-11 respectively.

Based on the presented data in aforementioned tables and figures, we can rank the performance measures of various eight control charts including the seven adaptive models and the FP control chart for broad ranges of shifts in means at achieved optimal points (Tables 4.2.2 to 4.2.4).

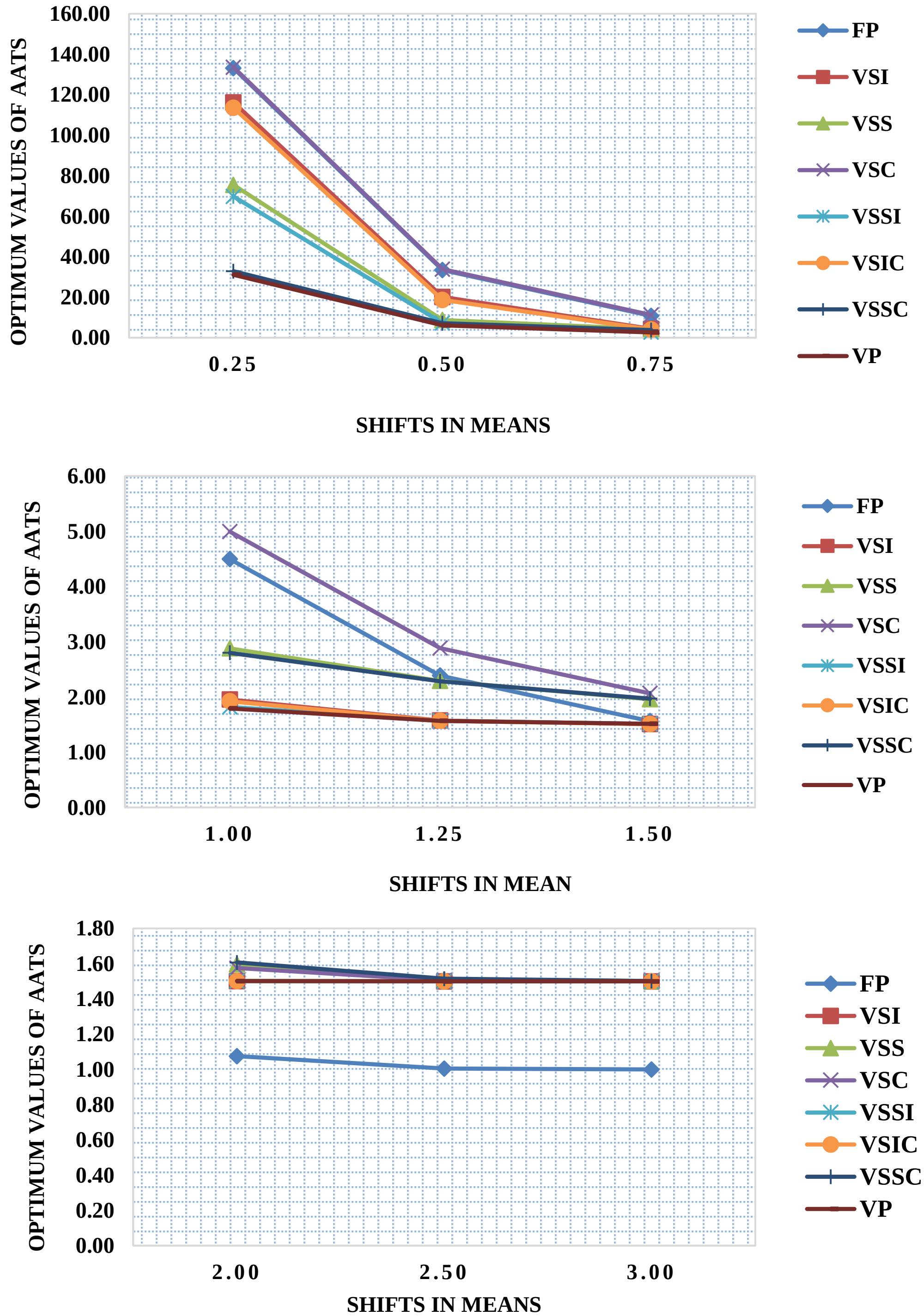

Figure 4-9: The optimum values of AATS for various ranges (small, medium, and relatively large) of shifts in mean for seven adaptive models and the FP control chart

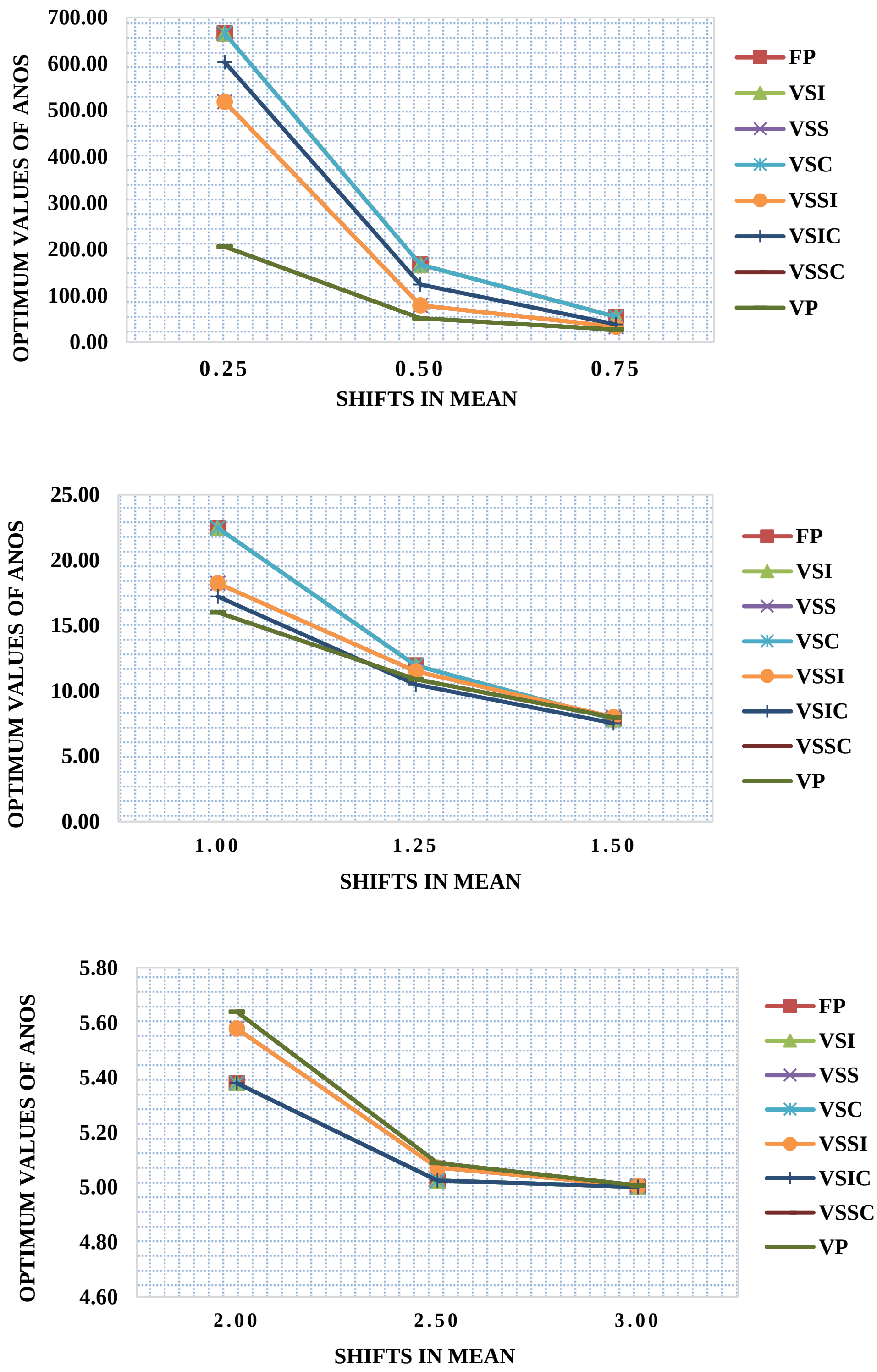

Figure 4-10: The optimum values of ANOS for various ranges(small, medium, and relatively large) of shifts in mean with respect to seven adaptive control charts and the FP chart

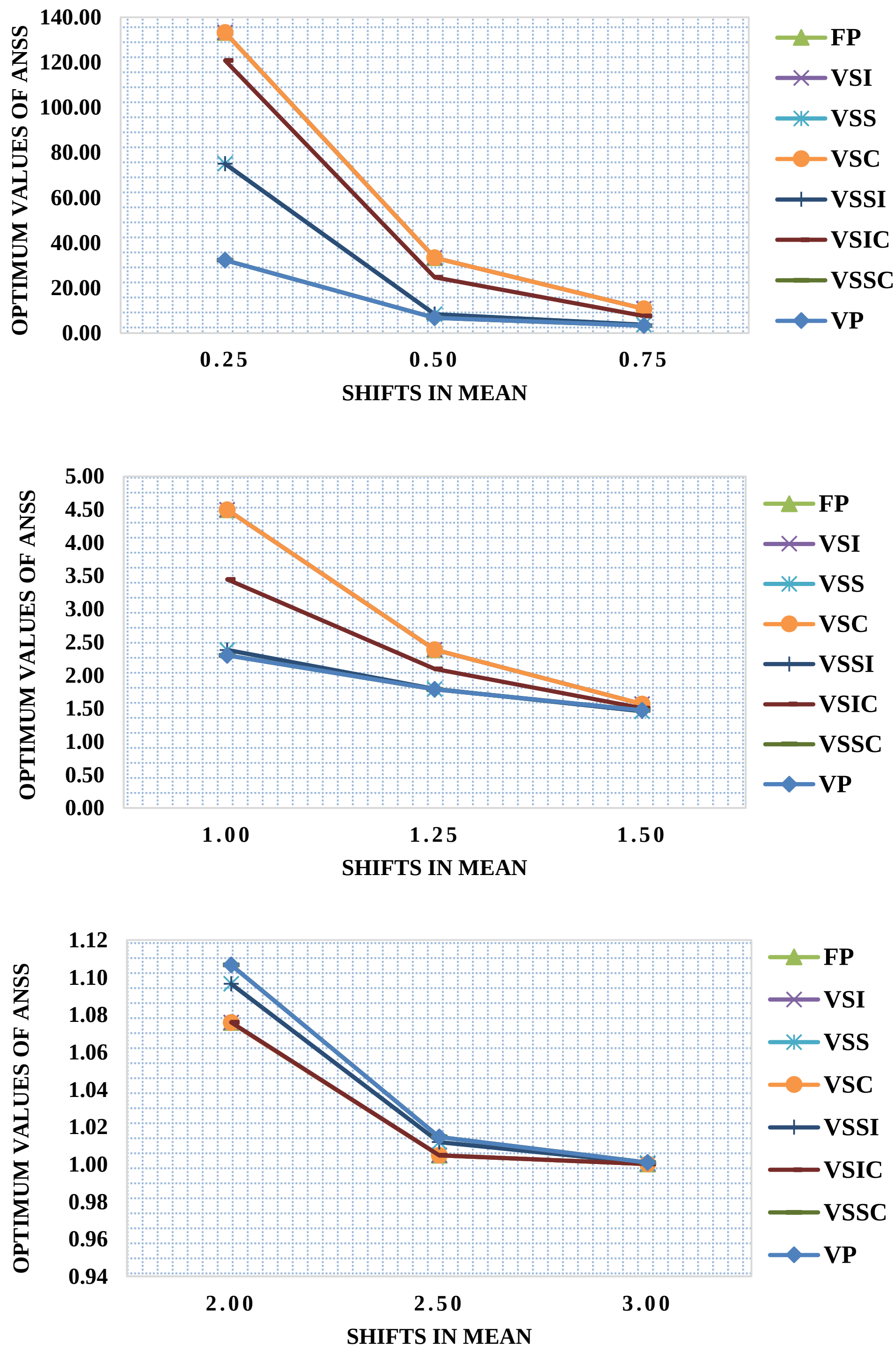

Figure 4-11: The optimum values of ANSS for various ranges (small, medium, and relatively large) of shifts in mean with respect to the seven various adaptive models and the FP control chart

Table 4.2.2: Ranking obtained optimum AATS values for various models with respect to small, medium, and relatively large shifts in mean

Optimum AATS	Ranks for various shifts in mean of δ								
	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
$AATS_{VP}$	1	1	1	1	1	3	4	5	3
$AATS_{VSSC}$	2	2	3	5	5	7	7	8	6
$AATS_{VSSI}$	3	3	2	2	2	4	3	4	3
$AATS_{VSS}$	4	4	5	6	6	6	6	7	5
$AATS_{VSIC}$	5	5	4	3	3	1	2	3	2
$AATS_{VSI}$	6	6	6	4	4	2	2	2	2
$AATS_{VSC}$	8	8	8	8	8	8	5	6	4
$AATS_{FP}$	7	7	7	7	7	5	1	1	1

Table 4.2.3: Ranking obtained optimum ANOS values for various models with respect to small, medium, and relatively large shifts in mean

Optimum ANOS	Ranks for various shifts in mean of δ								
	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
$ANOS_{VP}$	1	1	1	1	2	4	5	4	5
$ANOS_{VSSC}$	1	1	1	1	2	4	5	4	5
$ANOS_{VSSI}$	2	2	2	3	3	5	4	3	4
$ANOS_{VSS}$	2	2	2	3	3	5	4	3	4
$ANOS_{VSIC}$	3	3	3	2	1	1	3	2	3
$ANOS_{VSI}$	4	4	5	4	5	2	1	1	2
$ANOS_{VSC}$	4	4	5	4	5	2	1	1	2
$ANOS_{FP}$	5	4	4	5	4	3	2	1	1

Table 4.2.4: Ranking obtained optimum ANSS values for the eight control charts containing adaptive models and the FP chart with respect to small, medium, and relatively large shifts in mean

Optimum ANSS	Ranks for various shifts in mean of δ								
	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
$ANSS_{VP}$	1	1	1	1	1	2	4	4	4
$ANSS_{VSSC}$	1	1	1	1	1	2	4	4	4
$ANSS_{VSSI}$	2	2	2	2	2	1	3	3	3
$ANSS_{VSS}$	2	2	2	2	2	1	3	3	3
$ANSS_{VSIC}$	3	3	3	3	3	3	2	2	2
$ANSS_{VSI}$	4	4	4	4	4	4	1	1	1
$ANSS_{VSC}$	4	4	4	4	4	4	1	1	1
$ANSS_{FP}$	4	4	4	4	4	4	1	1	1

Moreover, when the decision makers prefer to obtain more information about the highest improvement percentage for the AATS measure, the following conclusions can be utilized based on Figure 4-12. They can have access to the exact values of performance measures and design parameters simultaneously using tables presented in this section earlier.

- The highest improvement percentage for the AATS measure can be assigned to the VP control chart for shifts in mean of $\delta \epsilon \{0.25, 0.50, 0.75, 1, 1.25\}$.
- The highest improvement percentage for the AATS measure can be assigned to the VSIC and the VSI control charts for a shift in mean of $\delta = 1.5$
- The improvement percentage has a negative value, or zero value for shifts in mean of $\delta \epsilon \{2, 2.5, 3\}$, which means that using a FP chart in such shifts in mean is more efficient than using other adaptive control charts.

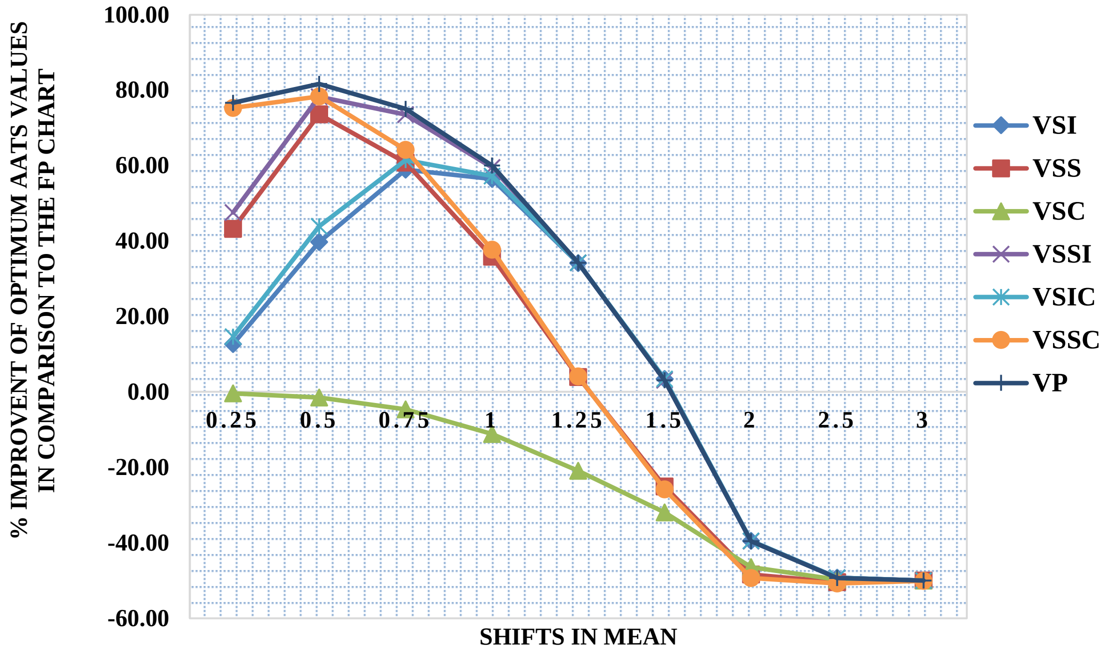

Figure 4-12: The improvement percentages of optimum AATS values for the seven adaptive models in comparision to the FP control chart

Once the decision makers would rather gain more information about the highest improvement percentage for the ANSS measure, the following conclusions can be taken into consideration in accordance with Figure 4-13:

- The highest improvement percentage for the ANSS measure can be assigned to the VSSC and the VP control charts for shifts in mean of $\delta \in \{0.25, 0.50, 0.75, 1, 1.25\}$.
- The highest improvement percentage for the ANSS measure can be assigned to the VSS and the VSSI control charts for the shift in mean of $\delta = 1.5$.

- The improvement percentage has a negative value, or zero value for shifts in mean of $\delta \epsilon \{2,2.5,3\}$, which means that using a FP chart in such shifts in mean is more efficient than using other adaptive control charts.

Figure 4-13: The improvement percentages of optimum ANOS values for the seven adaptive models in comparision to the FP control chart

Once the decision makers prefer to have more information about the highest improvement percentage for the ANOS measure, the following conclusions can be used based on Figure 4-14:

- The highest improvement percentage for the ANOS measure can be assigned to the VSSC and the VP control for shifts in mean of $\delta \epsilon \{0.25, 0.50, 0.75, 1\}$.

- The highest improvement percentage for the ANOS measure can be assigned to the VSIC control charts for shift in mean of $\delta = 1.25$.
- The improvement percentage has a negative value, or zero value for shifts in mean of $\delta \epsilon \{1.5,2,2.5,3\}$, which means that using a FP chart in such shifts in mean is more efficient than using other adaptive control charts.

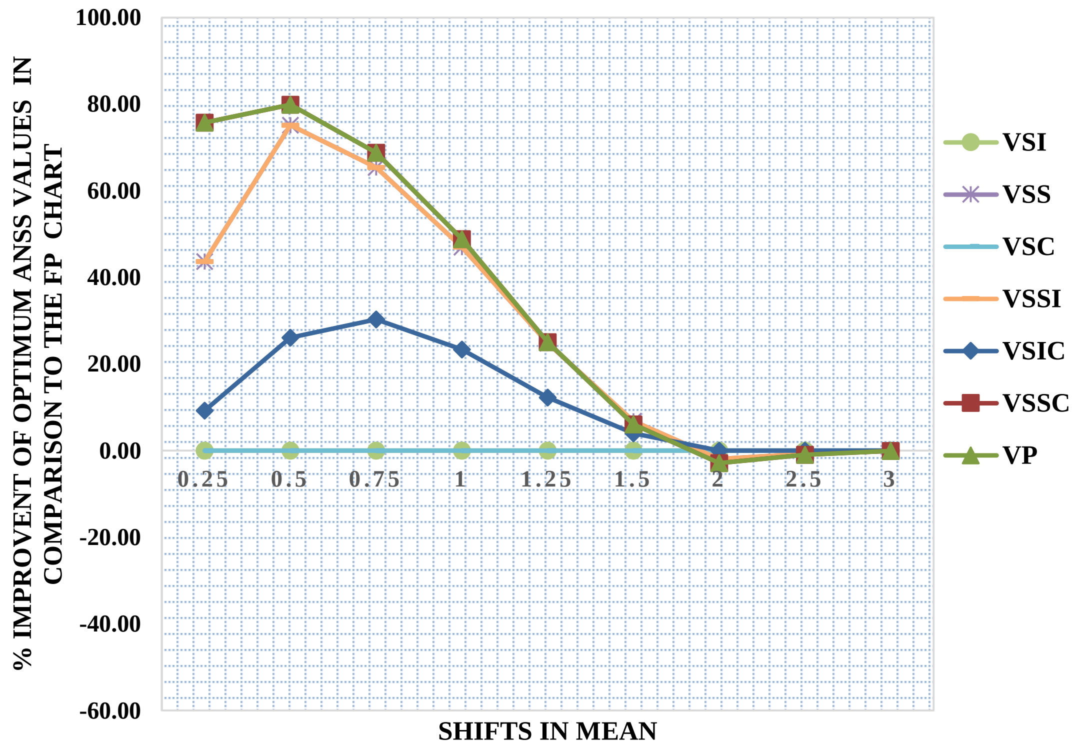

Figure 4-14: The improvement percentages of optimum ANSS values for the seven adaptive models in comparision to the FP control chart

4.3 Summary

In this research, unlike previous studies which concentrated on evaluating performance of adaptive control charts for a specific set of design parameters and used a forward perspective, we focused on a reverse standpoint. In order to gain more information about design parameters of optimal points with minimum values for performance measures of various seven adaptive control charts, a coded algorithm was proposed to search the entire response space. In this way, we concentrated on finding optimal minimum values of three major performance measures (AATS, ANOS, and ANSS) of various adaptive $\bar{X}$ control charts. For this purpose, we considered all possible combinations of design parameters and searched the entire feasible response space by using programming loops. Afterwards, at each obtained optimal minimum value for a given performance measure, the related values for other performance measures, design parameters, and improvement percentages in comparison to the FP control chart were evaluated for broad ranges of shifts in mean with respect to each adaptive control chart.

Based on obtained results, more information about the design parameters and value of all performance measures at optimal points were disclosed. The implementation of proposed methodology and achieved data in this paper, provide an efficient guideline for decision makers and quality managers to get more information about discrete optimal points in the response space in which performance measures of various adaptive control charts have their minimum values for broad ranges of shifts in mean.

Chapter 5

5 Evaluation of Recycling Opportunities and Waste Disposal Alternatives in a Health Care Supply Chain Using an Intuitionistic Fuzzy VIKOR Method

The two objectives of this chapter are to evaluate recycling opportunities in health care supply chains/systems and present a new multi-criteria decision making technique based on intuitionistic fuzzy set theory and VIKOR method for assessing health care waste disposal technologies. Linguistic variables are utilized by decision makers to evaluate the ratings and weights for the determined criteria. The intuitionistic fuzzy weighted averaging (IFWA) operator is applied to aggregate individual opinions of decision makers into a group evaluation. The computational procedure of the proposed methodology is demonstrated through a case study of a hospital located in Ohio, U.S. Four health care waste treatment alternatives considered in this research entail incineration, steam sterilization, microwave, and landfilling. The proposed approach estimates the GHG reductions and potential economic benefit derived from increased recycling for the case study. In addition, analyzing the obtained results shows that steam sterilization and microwave technologies are the best alternatives for disposing health care wastes as they emit fewer pollutants and generate non-hazardous residues.

Health care wastes and health stream have steeply increased in recent decades as a result of increased population, number, and size of health care facilities, as well as the use of disposable medical products (Manga et al., 2011; Moreira et al., 2013; Dursun et al., 2011a; Dursun et al., 2011b; Liu et al., 2013; Abed-Elmdoust and Kerachian, 2012). In accordance with waste categorization for health care systems by WHO, major waste streams include general wastes, infectious wastes, pathological wastes, sharp wastes, wastes with high content of heavy metals, hazardous wastes, pharmaceutics wastes, and radioactive wastes as given in Table 5-1 (Ananth et al., 2010; Komilis et al., 2012; Liu et al., 2013). General waste is not regulated or defined as hazardous or potentially dangerous waste and does not require special handling or treatment. It can be dealt with via municipal waste disposal mechanisms. This kind of waste can also be evaluated for potential recycling opportunities. The rest of health care waste streams are regarded as special wastes that require special treatment and disposal (Lee et al., 2004; Windfeld and Brooks, 2015). Health care waste disposal is an issue of significant scale. The U.S. creates over 3.5 million tonnes of medical waste per year with an average disposal cost of $790 per tonne (Windfeld and Brooks, 2015). Planning of health care waste management is necessary to prevent waste from adversely affecting human and environmental health. For the successful implementation of any health care waste management plan, a fundamental prerequisite is the availability of sufficient and accurate information about the quantities and composition of the waste generated (Qdais et al., 2007). Controlling health care wasest is a very critical issue. Sustainability and the health of freshwater ecosystems are vital to insure their safe and continued use. Health care wastes can contaminate water resources and soil. The water resources which are close to the hospitals and health care centers are also subject to high intensity risk of contamination.

Daneshvar *et al.* (2016) focused on water quality and stream health and tried to disclose the interactions between socioeconomic variable such as and stream health. For this purpose, they applied regression models and evaluated the effects of spatial data resolution on environmental justice analysis with respect to stream health integrity. Seventeen socioeconomic/physiographic indicators representing population, household composition, racial composition of household, female headed households, housing, educational disadvantage, economic disadvantage, welfare receipt, and unemployment in addition to four stream health measures (including one fish and three macroinvertebrates indices) were utilized in their research.

There are some remedies for improving the water quality such as watershed management. Herman *et al.* (2015) introduced a new approach to improve stream health to a desirable condition at the lowest cost by optimizing the best management practice implementation plan. Several hydrological models including the Soil and Water Assessment Tool (SWAT) and Hydrologic Index Tool (HIT) were integrated and the results were used to develop a stream health model. SWAT model was calibrated and validated against daily streamflow data from nine US geological gauging stations for a 10-year-period while the stream health model was calibrated and validated against 193 biological monitoring sites operated by the Michigan Department of Natural Resources. They applied GA to guide the stream health model in order to design the watershed-scale management strategies that included five best management practices. Herman *et al.*

(2016) used GA for optimization of bioenergy crop selection and placement based on a stream health indicator. Daneshvar *et al.* (2015) compared multiple-point and single-point calibration performance by using SWATsoftware. They considred Saginaw River Watershed as a case study.

Javidi Sabbaghian *et al.* (2016) introduced the application of risk-based MCDM for selection of the best agriculture scenario for effective watershed management which results in better quality of water resources. They used trapezoidal fuzzy numbers for linguistic variables.

Abouali *et al.* (2016a) introduced a new MATLAB hydrological index tool as a high performance library to calculate 171 ecologically relevant hydrological indices. The software was developed with special emphasis on its computational performance and its application for big data sets, containing thousands of streams.

Another study was also conducted by Abouali *et al.* (2016b) on proposing a new two-phase modeling approach in order to model four biotic indices. For each of these indices and in the first phase, initial estimates were provided for both the predicted biotic index and the error of those predictions. In the second phase, initial estimates are combined with the predicted errors to get a final estimate for the biotic index.

To improve health care waste management, several studies have focused on selection of the appropriate health care waste disposal methods using MCDM techniques. Conventional MCDM techniques such as AHP have been employed in numerous case studies to assess proper technologies for health care waste treatment (Brent *et al.*, 2007; Hsu *et al.*, 2008; Karagiannidis *et al.*, 2010).

As the decision to select an optimal technology for the disposal of health care waste is a complicated multi-criteria decision analysis problem involving both qualitative and quantitative factors, recent studies have applied hybrid fuzzy logic based MCDM methods. Fuzzy logic based MCDM methods help to deal with uncertainty of information and the vagueness of decision makers' recognition. Dursun *et al.* (2011a) proposed MCDM techniques for conducting an analysis based on multi-level hierarchical structure and fuzzy logic for the evaluation of healthcare waste treatment alternatives. Hatami-Marbini *et al.* (2013) recommended fuzzy group Electre method for safety and health assessment in hazardous waste recycling facilities. They considered quantitative data and qualitative judgments provided by three decision makers in a case study and captured the ambiguity and impreciseness in their judgments with fuzzy logic. Liu *et al.* (2013) applied a VIKOR-based fuzzy method to assess four possible treatment technologies including incineration, steam sterilization, microwave, and landfill in accordance with defined criteria. In their next study, they focused on the integration of fuzzy multi-objective ratio analysis with DEMATEL method for the same case study (Liu *et al.*, 2015).

Although fuzzy numbers can represent the vagueness of ‘‘agreement’’, they cannot depict the ‘‘disagreement’’ of the decision makers and previous studies on selection of optimal technologies for health care waste disposal have not dealt with this matter. To tackle with this gap, in this chapter we focus on recycling opportunities in health care waste streams and propose a hierarchical multi-criteria group decision making model based on IFSs theory and VIKOR method to choose optimal technologies for disposing non-recyclable wastes in health care supply chains/systems. We use the concept of IFSs theory and linguistic values to overcome the uncertainty. IFSs have revealed definite merits in treating vagueness and uncertainty in comparison to fuzzy sets theory that cannot consider hesitancy degree of decision makers (Bansal *et al.* 2014; Datta *et al.*, 2013). IFSs enable us to model unknown information utilizing another degree called the degree of hesitation. So, in practical situations where the decision makers are unsure about the preferences, IFSs would be an appropriate tool to get them opinions compared to fuzzy sets. IFSs can represent three grades of membership function i.e.; membership degree, non-membership degree, and hesitancy degree (Liu and Wang, 2007; Xu and Liao, 2013, 2015, Govindan *et al.*, 2015).

Utilizing VIKOR method, which is one of beneficial MCDM techniques, enables us to achieve compromise solutions for a problem with conflicting criteria such as evaluation of waste disposal alternatives in health care systems. The compromise solution is a feasible solution, which is the closest to the ideal, and a compromise denotes an agreement established by mutual concessions. The key benefits of the VIKOR method are that it introduces the multi-criteria ranking index based on the particular measure of "closeness" to the ideal solution, and the obtained compromise solution provides a maximum group utility for the "majority" and a minimum individual regret for the "opponent" (Opricovic, 2011; Liu *et al.*, 2013; Mazdeh *et al.*, 2013). An extension of the VIKOR in intuitionistic fuzzy environment result in coping with the both tangible and intangible criteria and to determine the appropriate treatment alternatives for the health care waste disposal. We also apply an IFWA to aggregate the individual opinions of decision makers.

The rest of the chapter is organized as follows: in section 5.1, we present a generalized conceptual model to determine recycling opportunities and select the best treatment technology/technologies for waste disposal in a health care supply chain/system. In section 5.2 and section 5.3, we review some basic definitions of IFSs theory and VIKOR method successively. In section 5.4, we present the intuitionistic fuzzy group VIKOR method proposed in this study. In section 5.5, we demonstrate the application of the proposed method for evaluation of recycling opportunities and assessment of waste disposal alternatives in a hospital located in Ohio, Toledo area. We also present the achieved results in this section. In section 5.6, we summarize our conclusions.

Table 5.1: Major healthcare waste streams

Health care waste category	Examples
a) General wastes	Wastes derived from normal inpatient wards, outpatient examination rooms, first aid areas, administration, cleaning services, kitchens, stores, and workshops.
b) Infectious wastes	Potentially infectious wastes that require special management inside and outside the health care system such as microbiological laboratory wastes (blood and blood containers, Serologic wastes, etc.), discarded surgery wastes, and air filters that contain bacteria and viruses.
c) Pathological wastes	Tissues, organs, and fluids removed during surgery or autopsy medical procedure.
d) Sharp wastes	Needles, syringes, blood vials, etc.
e) Wastes with high content of heavy metals	Batteries, broken thermometers, blood-pressure gauges, etc.
f) Hazardous wastes	Wastes that are subject to special handling because of their physical /chemical properties or legal reasons such as hazardous chemicals.
g) Pharmaceutics wastes	Waste entailing pharmaceuticals that are expired or no longer needed; items contaminated by or containing pharmaceuticals (bottles, boxes).
h) Radioactive wastes	Waste containing radioactive substances (e.g. unused liquids from radiotherapy or laboratory research; contaminated glassware and packages).

5.1 Research Approach

In this section, a generalized conceptual model to determine recycling opportunities and select the best treatment technology/technologies for waste disposal in a health care system is presented (Figure 5-1). The conceptual model begins with the identification of the MSW streams at the health care system that can be completed via several methods such as data provided by the facility through waste hauling and historical records. Moreover, by examining typical waste containers at the health care system an estimate of the overall MSW stream can be determined. A waste audit is necessary to determine annual MSW generation in terms of volume, tonnages, and composition. The process involves measuring the size of each container, and based on the number of times that the container is emptied and material composition, extrapolating the annual MSW stream generated from the container. Then, based on current recycling levels, the amount of recyclables disposed at landfills can be determined. This data helps the health care system in regards to changes in the present waste management programs to capture the most recyclables and reduce the waste hauling expenses.

Estimation of the GHG emissions can also be done either in MTCE or metric tons of carbon dioxide equivalent ($MTCO_2$ Eq.). Table 5.1.1 represents the GHG emissions associated with managing one short ton of respective MSW material. These factors were provided from the EPA WARM (EPA, 2015b). The negative values in the table represent the reduction in emissions. Overall emissions from a waste component can be computed by using the following equation:

$$E_x = (W_x^l \times F_x^l) + (W_x^r \times F_x^r)$$

Equation 5.1-1

Where E_x is the overall emissions from waste component x, W_x^l is the overall weight of waste component x that is being landfilled. F_x^l refers to GHG emission factor for waste component x when recycled. For instance, at a certain facility, if it is evaluated that 4 tonnes of PET are generated and disposed at a landfill, the carbon emissions associated with the PET is 0.04 MCTE. If the same quantity of PET is captures and recycled the emissions reduction will be 1.72 rather than 1.68 MCTE. This is due to the fact that these 4 tonnes of PET are not landfilled; this reduces an additional 0.04 MCTE as a result of recycling. Based on the waste generation levels at a health care system, various recycling opportunities can exist. The major waste streams can be identified and all potential possibilities for recycling can be studied for the most feasible economic and operational options. Once, the recyclables at the health care system are estimated, potential revenue from the sale of these materials on the commodity market can be computed on the basis of the current market value. Emissions reduction from recycling can be estimated, too. In the next stage, it is also necessary to evaluate various waste disposal alternatives for non-recyclable materials by using efficient MCDM methods. In this study, we propose intuitionistic fuzzy based VIKOR method.

Table 5.1.1: GHG emission factors for list of materials commonly recycled in Lucas County, Toledo, Ohio

Material	GHG emission factors if recycled (MTCE/metric ton)	GHG emission factors if landfilled (MTCE/metric ton)
Mixed office paper	-0.93	0.12
Cardboard	-0.85	0.1
Newspaper	-0.73	-0.24
PET (1)	-0.42	0.01
HDPE(2)	-0.38	0.01
Aluminum cans	-3.72	0.01

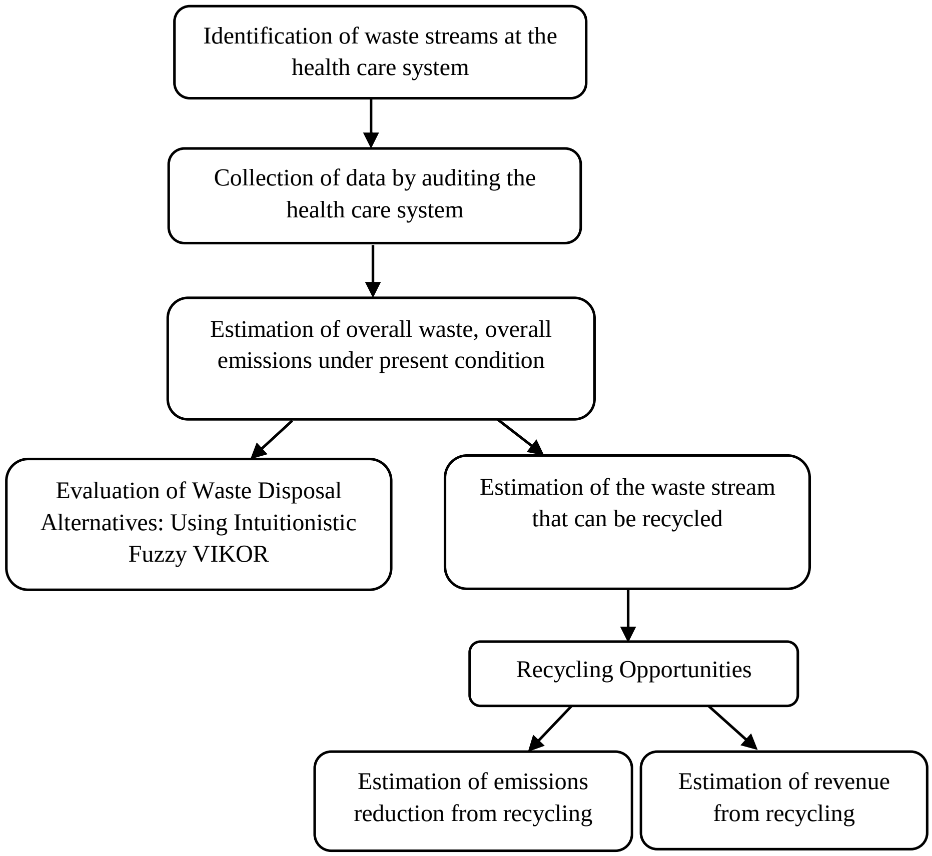

Figure 5-1: Flow chart of generalized model to evaluate waste disposal alternatives, recycling opportunities, GHG emission, and revenue from recycling program

5.2 Intuitionistic Fuzzy Sets Approach

In order to deal with the vagueness, ambiguity and subjectivity of human judgment, fuzzy sets theory (Bellman and Zadeh, 1965) was introduced to express the linguistic terms in decision making process. Up to now, many new approaches and theories treating imprecision and uncertainty have been proposed. Among them intuitionistic fuzzy sets (IFSs) introduced by Atanassov (1986) have been considered as suitable ways in modeling many real situations. IFSs are characterized by two functions expressing the degree of belongingness and the degree of non-belongingness, respectively. In the following, for the purpose of reference, some important definitions and notations of IFSs theory will be reviewed.

Definition 1. IFS A in a finite set X can be defined as (Atanassov, 1986, Nikjoo and Saeedpoor, 2014):

$$A = \{ \prec x, \mu_A(x), v_A(x) \succ | \, x \in X \}$$

Equation 5.2-1

Here $\mu_A(x), v_A(x) : X \to [0,1]$ are membership function and non-membership function sequentially and $0 \le \mu_A(x) + v_A(x) \le 1$. A third parameter of IFS is IF index of $\pi_A(x)$ that implies the hesitation degree of whether x belongs to A or not.

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x)$$

Equation 5.2-2

The value of $\pi_A(x)$ indicates whether the knowledge about x is more certain or uncertain. Moreover, when for all elements of universe $\mu_A(x) = 1 - v_A(x)$ or in other word IF index is changed into zero, IFS A is transformed into an ordinary fuzzy set (Liu and Wang, 2007).

Definition 2. Let A and B are IFSs of the set *X*, then some operations are defined as follows (Atanassov, 1986):

$$A \otimes B = \left\{ \mu_A(x).\mu_B(x), v_A(x) + v_B(x) - v_A(x).v_B(x) \mid x \in X \right\}$$

Equation 5.2-3

$$A \oplus B = \left\{ \mu_A(x) + \mu_B(x) - \mu_A(x).\mu_B(x), v_A(x).v_B(x) \mid x \in X \right\}$$

Equation 5.2-4

$$A \bigcup B = \left\{ \min(\mu_A(x), \mu_B(x)), \max(v_A(x), v_B(x)) \mid x \in X \right\}$$

Equation 5.2-5

$$A \bigcap B = \left\{ \max(\mu_A(x), \mu_B(x)), \min(v_A(x), v_B(x)) \mid x \in X \right\}$$

Equation 5.2-6

5.3 VIKOR Method

Opricovic and Tzeng (2004) developed the VIKOR method for multi-criteria decision making. This technique focuses on ranking and selecting from a set of alternatives, and determines compromise solutions for a problem with conflicting criteria, which can help the decision makers to reach a final decision. (Opricovic and Tzeng 2004). Here, the compromise solution is a feasible solution which is the closest to the ideal. It introduces the multi-criteria ranking index based on the particular measure of closeness to the ideal solution. If every alternative i is denoted as A_i then multi-criteria ranking index is shown in the Equation 5.2-7 below for $1 \le P < \infty$:

$$L_{P,i} = \left\{ \sum_{j=1}^{n} \left[W_j (f_j^* - f_{i,j}) / (f_j^* - f_j^-) \right]^P \right\}^{1/p} \quad i = 1, 2, \ldots, m$$

Equation 5.2-6

Within the VIKOR method $L_{1.j}$ and $L_{\infty.j}$ are used to formulate ranking measure. $L_{1.j}$ is accounted for "concordance" and can provide information about the maximum group utility or majority. Similarly, $L_{\infty.j}$ is interpreted as "discordance" and provides information about the minimum individual regret of the "opponent". Furthermore, in comparison to TOPSIS method, another MCDM method, which is based on aggregating function representing closeness to ideal, VIKOR method consider the relative importance of the distances from ideal points. Also, the normalized value in the VIKOR method does not depend on the evaluation unit of criterion function, whereas the normalized values by vector normalization in the TOPSIS method may depend on the evaluation unit methods (Chu et al., 2007).

5.4 Intuitionistic Fuzzy VIKOR

In this section, we focus on hybridization of the VIKOR with fuzzy intuitionistic approach. Let $A=\{A_1,A_2,...,A_m\}$ be a set of alternatives and $X=\{x_1,x_2,...,x_n\}$ a set of criteria, the intuitionistic fuzzy VIKOR method described next through a series of structured and successive steps.

Step 1. In this stage, the weights of decision makers are determined. Assuming that there are L decision makers (DMs) ,their importance are expressed as linguistic terms in intuitionistic fuzzy numbers and $D_K=[\mu_k,v_k,\pi_k]$ is considered as an intuitionistic fuzzy number for rating of k^{th} DM, then the weight of k^{th} DM can be obtained as Equation 5.4-1 for $\sum_{k=1}^{L} \lambda_k = 1$ (Boran *et al.*, 2009).

$$\lambda_k = \frac{\left(\mu_k + \pi_k \left(\frac{\mu_k}{\mu_k + v_k}\right)\right)}{\sum_{k=1}^{L}\left(\mu_k + \pi_k \left(\frac{\mu_k}{\mu_k + v_k}\right)\right)}$$

Equation 5.4-1

Step 2. In this stage, the aggregated intuitionistic fuzzy decision matrix based on the opinions of DMs is formed. Let $R^{(k)} = \left(r_{i,j}{}^{(k)}\right)_{m\times n}$ is an intuitionistic fuzzy decision matrix of each DM and the λ set $\lambda = \{\lambda_1, \lambda_2, ..., \lambda_L\}$ where $\sum_{k=1}^{L} \lambda_k = 1$ and $\lambda_k \in [0,1]$ shows the weight of each DM. In order to form an aggregated intuitionist fuzzy decision matrix, we have used the intuitionistic fuzzy weighted averaging (IFWA) operator which is proposed by Xu (2007), therefore we will have: $R = \left(r_{i,j}\right)_{m\times n}$ where:

$$\begin{aligned} r_{i,j} &= IFWA_{\lambda}\left(r_{i,j}{}^{(1)}, r_{i,j}{}^{(2)}, ..., r_{i,j}{}^{(L)}\right) = \lambda_1 r_{i,j}{}^{(1)} \oplus \lambda_2 r_{i,j}{}^{(2)} \oplus \lambda_3 r_{i,j}{}^{(3)} \oplus ... \oplus \lambda_L r_{i,j}{}^{(L)} \\ &= \left[1 - \prod_{k=1}^{L}(1-\mu_{i,j}{}^{(k)})^{\lambda_k}, \prod_{k=1}^{L}(v_{i,j}{}^{(k)})^{\lambda_k}, \prod_{k=1}^{L}(1-\mu_{i,j}{}^{(k)})^{\lambda_k} - \prod_{k=1}^{L}(v_{i,j}{}^{(k)})^{\lambda_k}\right] \end{aligned}$$

Equation 5.4-2

Here $r_{i,j} = (\mu_{A_i}(x_j), v_{A_i}(x_j), \pi_{A_i}(x_j))$, $i = 1, 2, ..., m$, $j = 1, 2, ..., n$ and the aggregated intuitionist fuzzy decision matrix will be defined as:

$$R = \begin{bmatrix} r_{1,1} & \cdots & r_{1,m} \\ \vdots & r_{i,j} & \vdots \\ r_{n,1} & \cdots & r_{n,m} \end{bmatrix}$$

Equation 5.4-3

Step 3. In this stage, the weights of criteria are defined. In order to achieve W which indicates a set of grades of importance, all of the DMs' opinion related to the importance of criterion must be combined together. If we assume that $W_j^{(k)} = \left[\mu_j^{(k)}, v_j^{(k)}, \pi_j^{(k)}\right]$ is an intuitionistic fuzzy number which is allocated to the criterion x_j by k^{th} DM, then the weights of criteria can be calculated by using IFWA operator as below:

$$W_j = IFWA_\lambda\left(W_j^{(1)}, W_j^{(2)}, \ldots, W_j^{(L)}\right) = \lambda_1 W_j^{(1)} \oplus \lambda_2 W_j^{(2)} \oplus \lambda_3 W_j^{(3)} \oplus \ldots \oplus \lambda_L W_j^{(L)}$$
$$= \left[1 - \prod_{k=1}^{L}(1-\mu_{i,j}^{(k)})^{\lambda_k}, \prod_{k=1}^{L}(v_{i,j}^{(k)})^{\lambda_k}, \prod_{k=1}^{L}(1-\mu_{i,j}^{(k)})^{\lambda_k} - \prod_{k=1}^{L}(v_{i,j}^{(k)})^{\lambda_k}\right]$$

Equation 5.4-4

Where $W = \left[W_1, W_2, \ldots, W_j\right]$, $W_j = \left[\mu_j, v_j, \pi_j\right]$, $j = 1, 2, \ldots, n$

Step 4. In this stage, the aggregated weighted intuitionistic fuzzy decision matrix is formed. After determining the weights of criteria and formation of aggregated intuitionist fuzzy decision matrix, each element of aggregated weighted intuitionistic fuzzy decision matrix will be computed according to Equation 4 as follows:

$$R \otimes W = \left\{\langle x, \mu_{A_i}(x).\mu_w(x), v_{A_i}(x) + v_W(x) - v_{A_i}(x).v_W(x)\rangle \mid x \in X\right\}$$

Equation 5.4-5

The $\pi_{A_i.W}(x)$ will be considered as follows:

$$\pi_{A_i.W}(x) = 1 - v_{A_i}(x) - v_W(x) - \mu_{A_i}(x) - \mu_w(x) + v_{A_i}(x).v_W(x)$$

Equation 5.4-6

Then, the aggregated weighted intuitionistic fuzzy decision matrix will be defined as below:

$$R \otimes W = \begin{bmatrix} r_{1,1}' & \cdots & r_{1,m}' \\ \vdots & r_{i,j}' & \vdots \\ r_{n,1}' & \cdots & r_{n,m}' \end{bmatrix}$$

Where $r_{i,j}^{'} = (\mu_{i,j}', v_{i,j}', \pi_{i,j}') = (\mu_{A_i w}(x_j), v_{A_i w}(x_j), \pi_{A_i w}(x_j))$

Equation 5.4-7

Step 5. In this stage, the best and the worst values (f_i^*, f_i^-) for each criterion are determined. Assuming that J_1 refers to the benefit criteria, J_2 refers to the cost criteria, for $j = 1, 2, ..., n$ we will have:

$$f_j^* = \max_i \; x_{i,j} = ((\mu_j^* = \max_i \mu_{A_i w}(x_j), v_j^* = \min_i v_{A_i w}(x_j), \pi_j^* = 1 - \mu_j^* - v_j^*) \mid j \in J_1)$$

Equation 5.4-8

$$f_j^* = \min_i x_{ij} = ((\mu_j^* = \min_i \mu_{A_i w}(x_j), v_j^* = \max_i v_{A_i w}(x_j), \pi_j^* = 1 - \mu_j^* - v_j^*) \mid j \in J_2)$$

Equation 5.4-9

$$f_j^- = \min_i x_{ij} = ((\mu_j^- = \min_i \mu_{A_i w}(x_j), v_j^- = \max_i v_{A_i w}(x_j), \pi_j^- = 1 - \mu_j^- - v_j^-) \mid j \in J_1)$$

Equation 5.4-10

$$f_j^- = \max_i x_{ij} = ((\mu_j^- = \max_i \mu_{A_i w}(x_j), v_j^- = \min_i v_{A_i w}(x_j), \pi_j^- = 1 - \mu_j^- - v_j^-) \mid j \in J_2)$$

Equation 5.4-11

Step 6. In this stage, the values of S_i which refers to the sum of deviations and R_i which refers to maximum deviation are computed.

$$S_i = \sum_{j=1}^{n} \left[\frac{\left|\mu_{A^*w}(x_j) - \mu_{A_iw}(x_j)\right| + \left|v_{A^*w}(x_j) - v_{A_iw}(x_j)\right| + \left|\pi_{A^*.W}(x_j) - \pi_{A_i.W}(x_j)\right|}{\left|\mu_{A^*w}(x_j) - \mu_{A^-w}(x_j)\right| + \left|v_{A^*w}(x_j) - v_{A^-w}(x_j)\right| + \left|\pi_{A^*.W}(x_j) - \pi_{A^-.W}(x_j)\right|} \right]$$

Equation 5.4-12

$$R_i = \max_j \left[\frac{\left|\mu_{A^*w}(x_j) - \mu_{A_iw}(x_j)\right| + \left|v_{A^*w}(x_j) - v_{A_iw}(x_j)\right| + \left|(\pi_{A^*.w}(x_j) - \pi_{A_i.w}(x_j)\right|}{\left|\mu_{A^*w}(x_j) - \mu_{A^-w}(x_j)\right| + \left|v_{A^*w}(x_j) - v_{A^-w}(x_j)\right| + \left|\pi_{A^*.w}(x_j) - \pi_{A^-.w}(x_j)\right|} \right]$$

Equation 5.4-13

Step 7. In this stage, the value of Q_i is calculated as below and the alternatives are ranked by sorting the values of S_i, R_i, Q_i in ascending order.

$$Q_i = v \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - v) \frac{(R_i - R^*)}{(R^- - R^*)}$$

Equation 5.4-14

Here $S^* = \min_i S_i, R^* = \min_i R_i, R^- = \max_i R_i$, and v is introduced as a weight for the strategy of maximum group utility, whereas $(1-v)$ indicates the weight of the individual regret.

Step 8. In this stage, the alternative A' which has the best value of Q_i (minimum value) is proposed as a compromise solution if the following two conditions are satisfied. First: Acceptable advantage:

$$Q(A'') - Q(A') \geq DQ$$

Equation 5.4-15

Here A'' is the alternative with second position in the ranking list by Q_i and $DQ = \frac{1}{m-1}$ (m is the number of alternatives). Second: Acceptable stability in decision making: Alternative A' must also be the best ranked by S or/and R.

If one of the conditions is not satisfied, then a set of compromise solutions is proposed, which consists of Alternatives A' and A'' if only second condition is not satisfied, or Alternatives $A', A'', \ldots, A^M$ if the first condition is not satisfied; A^M is determined by the relation $Q(A^M) - Q(A') < DQ$ for maximum M (the positions of these alternatives are ‘‘in closeness”).

5.5 Case Study and Achieved Results

The proposed method was applied to a hospital located in Ohio, Toledo to evaluate waste disposal alternatives in health care systems. The solid waste assessment team of the BWRAP, sustainability laboratory of MIME department at University of Toledo, had the opportunity to conduct a recycling survey at a hospital located in Ohio, Toledo. The BWRAP is a joint partnership between the Lucas county solid waste management district and the University of Toledo. This hospital could accommodate over 300 patients. A total of 530 solid waste containers were utilized in different areas at this hospital. The procedure used to estimate the annual solid waste streams at this hospital involved a large sampling of waste containers in several areas (Fig.5-2). The annual volume of waste generated was estimated and using the standard densities, the volumes were converted to the annualized weights and compositions as displayed in Table 5.5.1 and Figure 5-3.

Figure 5-2: Some samples of inspected containers

Table 5.5.1: Annual amounts of municipal solid waste generated at the studied hospital

Component	Metric Tons per Year	Percent of total	Metric tons recycled	Metric tons not recycled
Waste Streams That Can Be Recycled				
Mixed Office Paper	58.70	12.01%	0	58.70
Newspaper	72.90	14.92%	0	72.90
Cardboard	8.30	1.70%	0	8.30
Aluminum Cans	16.60	3.40%	0	16.60
PET (1)	22.00	4.50%	0	22.00
HDPE (2)	81.20	16.62%	0	81.20
Waste Streams That Cannot Be Recycled				
Non-recyclable/food waste	228.90	46.85%	0	219.10
Total	488.60	100.00%	0	488.60

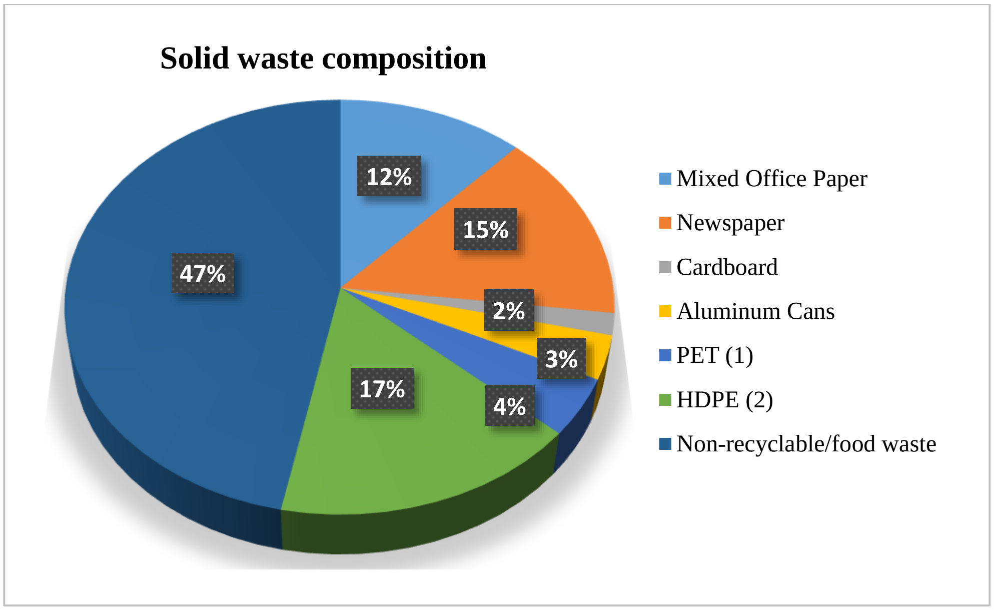

Figure 5-3: Case study solid waste composition

The team also evaluated the GHG emissions generated from each material by using GHG emission factors from Table 5.1.1. This evaluation is shown in Table 5.5.2. Table 5.5.3 displays the GHG emissions if additional materials are captured and recycled. Figure 5-4 shows the amount of emissions from landfilling and emissions reduction after recycling for the studied hospital. Recycling mixed office paper, aluminum cans, newspapers, and high-density polyethylene (HDPE) will be associated with significant GHG emission reduction of 61.0491 MTCE, 61.9180 MTCE, 35.7210 MTCE, and 31.6680 MTCE successively. Additional annual revenue generated from recycling are shown in Table 5.5.4. The net revenue generated when all the recyclable waste components are recycled is approximately $36,973 per year. From the emissions standpoint, if the studied hospital recycles all of the potentially recyclable material, the overall emissions will reduce considerably from 30.4890 MTCE to -177.2121 MTCE.

Table 5.5. 2: GHG emissions under present conditions

Component	Metric tons landfilled per year	Metric tons recycled per year	Emissions from landfilling per year (MTCE)	Emissions from recycling per year (MTCE)
Mixed Office Paper	58.70	0.00	7.0440	0.00
Newspaper	72.90	0.00	-17.4960	0.00
Cardboard	8.30	0.00	0.8300	0.00
Aluminum Cans	16.60	0.00	0.1660	0.00
PET (1)	22.00	0.00	0.2200	0.00
HDPE (2)	81.20	0.00	0.8120	0.00
Non-recyclable/food waste	228.90	0.00	38.9130	0.00

Table 5.5.3: GHG emissions if recyclable materials are recycled

Component	Metric tons landfilled per year	Metric tons recycled per year	Emissions from landfilling per year (MTCE)	Emissions after recycling per year (MTCE)	Emission reduction (MTCE)
Mixed Office Paper	0.00	58.70	0.00	-54.0051	61.0491
Newspaper	0.00	72.90	0.00	-53.217	35.7210
Cardboard	0.00	8.30	0.00	-7.0550	7.8850
Aluminum Cans	0.00	16.60	0.00	-61.7520	61.9180
PET (1)	0.00	22.00	0.00	-9.2400	9.4600
HDPE (2)	0.00	81.20	0.00	-30.856	31.6680
Non-recyclable/food waste	228.90	0.00	38.9130	0.00	0.00

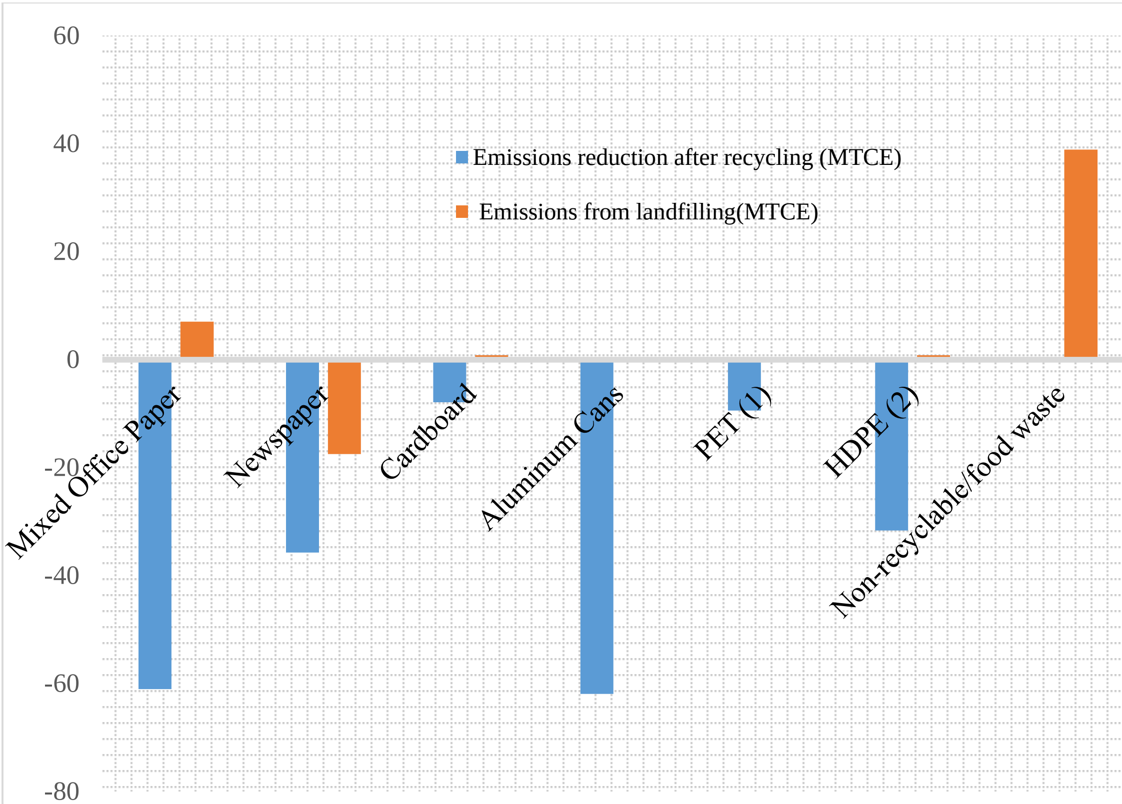

Figure 5-4: Emissions from landfilling and Emissions reduction after recycling for the case study

Table 5.5. 4: Total additional revenue generated from increase recycling

Component	Metric tons recycled per year	Current Market Value per ton in USA Midwest	Revenue in dollars from sale of recyclables
Mixed Office Paper	58.70	$40	$2,348
Newspaper	72.90	$30	$2,178
Cardboard	8.30	$90	$747
Aluminum Cans	16.60	$600	$9,960
PET (1)	22.00	$250	$5,500
HDPE (2)	81.20	$200	$16,240
Non-recyclable/food waste	0.00	-	-
Total	259.70	-	$36,973

In the following stage, four potential treatment technologies (alternatives) have been considered to dispose health care wastes as follows:

A_1 : Incineration, A_2 : Steam sterilization, A_3 : Microwave, and A_4 : landfilling.
It is needed to choose the best alternative/alternatives and achieve a ranking for alternatives. To select the most preferred alternative, an expert committee of three decision makers DM1, DM2, and DM3 from different institutions and department including a waste disposal company, environmental engineering, and industrial engineering has been formed. On the basis of experts' viewpoint and studied literature (Dursun *et al.*, 2011a; Liu *et al.*, 2013; Liu *et al.*, 2015) environmental, economic, technical, and social criteria with their related sub-criteria are recognized as Figure 5-5.

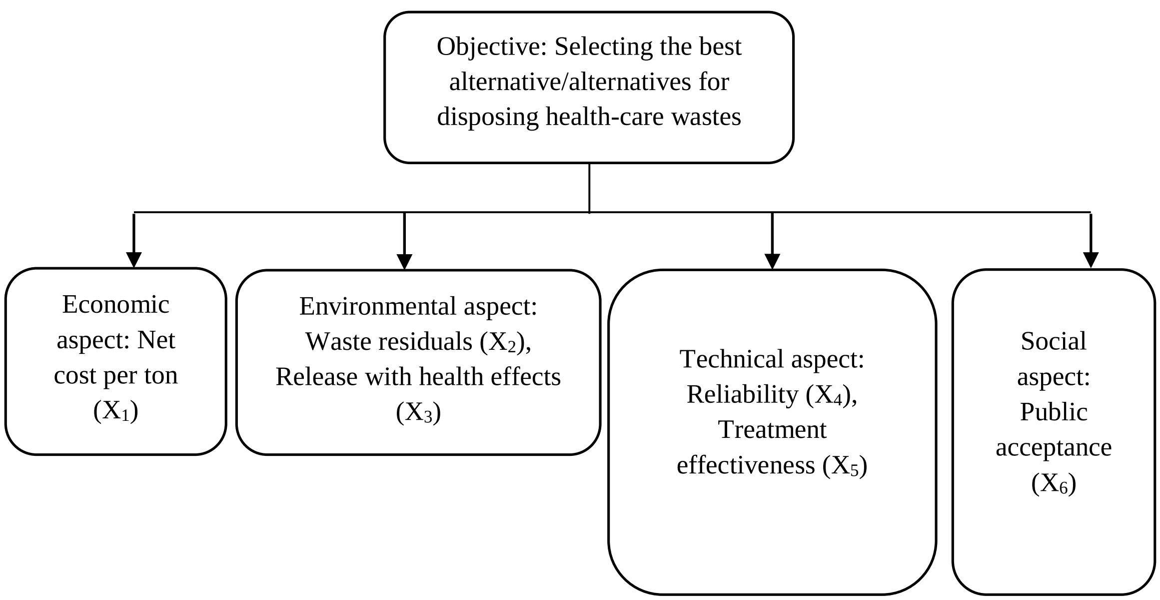

Figure 5-5: Defined criteria and their related sub-criteria for selecting the best alternative/alternatives for health care waste disposal

In order to obtain the decisions of the three decision makers on the four alternative health care waste disposal methods and on the weight of the defined six criteria, a number of interviews were conducted. They were asked to provide their opinions on the ratings of the alternatives with respect to each criterion and the importance weights of the criteria by using the linguistic variables. Here, the VIKOR-based intuitionistic fuzzy MCDM method is utilized to determine the best health care waste treatment alternative. This method consists of the following steps:

Step 1. Intuitionistic fuzzy number related to the linguistic terms used for the ratings of the decision makers and criteria are given in Table 5.5.5.

Table 5.5.5: Intuitionistic fuzzy number related to the linguistic variables for rating the criteria weights and decision makers' weights

Linguistic terms	Intuitionistic fuzzy number (μ, ν, π)
Very important (VI)	(0.90,0.10, 0.00)
Important (I)	(0.75,0.20, 0.05)
Medium (M)	(0.50,0.45, 0.05)
Unimportant (U)	(0.35,0.60, 0.05)
Very unimportant (VU)	(0.10,0.90, 0.00)

The linguistic terms and the weights related to the DMs' importance has shown in Table 5.5.6 and for calculating the weights of the decision makers, Equation 5.4-1 has been utilized.

$$\lambda_{DM1} = \frac{0.9}{0.9 + \left(0.75 + 0.05\frac{0.75}{0.95}\right) + (0.5 + 0.05\frac{0.50}{0.95})} = 0.406$$

$$\lambda_{DM2} = \frac{(0.5 + 0.05\frac{0.50}{0.95})}{0.9 + \left(0.75 + 0.05\frac{0.75}{0.95}\right) + (0.5 + 0.05\frac{0.50}{0.95})} = 0.238$$

$$\lambda_{DM3} = \frac{(0.75 + 0.05\frac{0.75}{0.95})}{0.9 + \left(0.75 + 0.05\frac{0.75}{0.95}\right) + (0.5 + 0.05\frac{0.50}{0.95})} = 0.365$$

Table 5.5. 6: The importance of decision makers and their weights

	DM1	DM2	DM3
Linguistic terms / Intuitionistic fuzzy number (μ, v, π)	Very important (VI) / (0.90,0.10, 0.00)	Medium (M)/ (0.50,0.45, 0.05)	Important (I)/ (0.75,0.20,0.05)
Obtained Weight (λ)	0.406	0.238	0.356

Step 2. Intuitionistic fuzzy numbers related to the linguistic terms which are shown in Table 5.5.7 are utilized to rate each alternative respecting each criterion by three decision makers.

Table 5.5.7: Linguistic variables for rating the alternatives with respect to criteria

Linguistic terms	Intuitionistic fuzzy numbers (μ, v, π)
Extremely high(EH)	(1.00,0.00,0.00)
Very very high(VVH)	(0.90,0.10, 0.00)
Very high(VH)	(0.80,0.10,0.10)
High(H)	(0.70,0.20,0.10)
Medium high(MH)	(0.60,0.30,0.10)
Medium(M)	(0.50,0.40,0.10)
Medium low(ML)	(0.40,0.50,0.10)
Low(L)	(0.25,0.60,0.15)
Very low (VL)	(0.10,0.75,0.15)
Very very low(VVL)	(0.10,0.90,0.10)

The assessment of the four alternatives on each criterion provided by the decision makers is presented in Tables 5.5.8-5.5.11.

Table 5.5.8: Linguistic assessments of alternatives provided by the five decision makers

Criterion	Alternatives	DM1	DM2	DM3
X_1	A_1	VH	VVH	VH
	A_2	MH	MH	L
	A_3	M	M	M
	A_4	MH	L	L
X_2	A_1	L	MH	L
	A_2	L	VVL	M
	A_3	L	VL	L
	A_4	MH	MH	VH
X_3	A_1	VVH	VH	H
	A_2	ML	L	VL
	A_3	L	L	L
	A_4	VH	H	VH
X_4	A_1	VVH	VH	H
	A_2	MH	H	H
	A_3	MH	MH	M
	A_4	L	M	M
X_5	A_1	VH	VH	H
	A_2	VH	VVH	MH
	A_3	H	M	M
	A_4	VVL	ML	L
X_6	A_1	VVH	H	H
	A_2	L	L	L
	A_3	L	ML	L
	A_4	VH	VH	VVH

As a result of this step, the aggregated intuitionistic fuzzy decision matrix based on aggregation of decision makers' opinions obtained as follows:

$$R = \begin{array}{c c} & \begin{array}{cccc} A_1 & A_2 & A_3 & A_4 \end{array} \\ \begin{array}{c} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \end{array} & \begin{bmatrix} (0.8326,0.0982,0.0692) & (0.5005,0.3827,0.1168) & (0.5028,0.3971,0.1002) & (0.4199,0.4513,0.1288) \\ (0.3557,0.5067,0.1376) & (0.3260,0.5676,0.1064) & (0.2185,0.5676,0.2139) & (0.6917,0.1990,0.1093) \\ (0.8271,0.1264,0.0465) & (0.2693,0.6021,0.1285) & (0.2517,0.5976,0.1507) & (0.7826,0.1158,0.1017) \\ (0.8271,0.1264,0.0465) & (0.6662,0.2327,0.1012) & (0.5692,0.3300,0.1008) & (0.4140,0.4679,0.1180) \\ (0.7711,0.1264,0.1025) & (0.7844,0.1466,0.0690) & (0.5957,0.2999,0.2044) & (0.2360,0.6743,0.0897) \\ (0.8096,0.1491,0.0413) & (0.2517,0.5976,0.1507) & (0.2904,0.5722,0.1374) & (0.8467,0.0982,0.0551) \end{bmatrix}^T \end{array}$$

$r_{1,1} = (0.8326,0.0982,0.0692)$ $r_{1,2} = (0.3557,0.5067,0.1376)$ $r_{1,3} = (0.8271,0.1264,0.0465)$

$r_{1,4} = (0.8271,0.1264,0.0465)$ $r_{1,5} = (0.7711,0.1264,0.1025)$ $r_{1,6} = (0.8096,0.1491,0.0413)$

$r_{2,1} = (0.5005,0.3827,0.1168)$ $r_{2,2} = (0.3260,0.5676,0.1064)$ $r_{2,3} = (0.2693,0.6021,0.1285)$

$r_{2,4} = (0.6662, 0.2327,0.1012)$ $r_{2,5} = (0.7844,0.1466,0.0690)$ $r_{2,6} = (0.2517, 0.5976,0.1507)$

$r_{3,1} = (0.5028,0.3971,0.1002)$ $r_{3,2} = (0.2185,0.5676,0.2139)$ $r_{3,3} = (0.2517, 0.5976,0.1507)$

$r_{3,4} = (0.5692,0.3300,0.1008)$ $r_{3,5} = (0.5957,0.2999,0.2044)$ $r_{3,6} = (0.2904,0.5722,0.1374)$

$r_{4,1} = (0.4199,0.4513,0.1288)$ $r_{4,2} = (0.6917,0.1990,0.1093)$ $r_{4,3} = (0.7826,0.1158,0.1017)$

$r_{4,4} = (0.4140,0.4679,0.1180)$ $r_{4,5} = (0.2360,0.6743,0.0897)$ $r_{4,6} = (0.8467,0.0982,0.0551)$

Step 3. The importance of the criteria represented as linguistic terms have been shown in Table 5.5.9. Opinions of decision makers on criteria were aggregated by using Equation 5.4-3 to determine the weight of each criterion.

Table 5.5.9: The importance weight of criteria

Criterion	DM1	DM2	DM3
X_1	I	I	VI
X_2	I	I	I
X_3	VI	I	VI
X_4	I	I	M
X_5	VI	I	I
X_6	I	M	M

$$W_{\{x_1,x_2,x_3,x_4,x_5,x_6\}} = \begin{bmatrix} (0.8230,0.1533,0.0237) \\ (0.7528,0.1974,0.0498) \\ (0.8779,01158,0.0063) \\ (0.6816,0.2655,0.0530) \\ (0.8294,0.1419,0.0215) \\ (0.6245,0.3220,0.0536) \end{bmatrix}^T$$

Step 4. The aggregated weighted intuitionistic fuzzy decision matrix has formed by utilizing Equation 5.2-3as follows:

$$R \otimes W = \begin{array}{c} \\ X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \end{array} \begin{array}{cccc} A_1 & A_2 & A_3 & A_4 \\ \end{array}$$

$$\begin{array}{c} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \end{array} \begin{bmatrix} (0.6853, 0.2364,0.0783) & (0.4119,0.4773,0.1108) & (0.4138,0.4895,0.0967) & (0.3456,0.5354,0.1190) \\ (0.2678,0.6041,0.1282) & (0.2454,0.6529,0.1016) & (0.1645,0.6176,0.2179) & (0.5207,0.3571,0.1222) \\ (0.7261,0.2276,0.0463) & (0.2365,0.6482,0.1154) & (0.2210,0.6441,0.1349) & (0.6870,0.2182,0.0948) \\ (0.5637,0.3583,0.7779) & (0.4540,0.4364,0.1096) & (0.3880,0.5079,0.1042) & (0.2822,0.6092,0.1086) \\ (0.6395,0.2567,0.1038) & (0.6506,0.2739,0.0756) & (0.4041,0.4043,0.1016) & (0.1958,0.7229,0.0814) \\ (0.5056,0.4231,0.0714) & (0.1572,0.7271,0.1157) & (0.1814,0.7099,0.1087) & (0.5287,0.3885,0.0827) \end{bmatrix}^T$$

Step 5-7. Net cost per ton (x_1), waste residuals (x_2), and release with health effects (x_3) are cost criteria; reliability (x_4), treatment effectiveness (x_5), and public acceptance (x_6) are benefit criteria. Thus, the values of f_j^* and f_j^- for all criteria ratings are determined as follows:

$$\begin{aligned} f_1^* &= (0.4119,0.4773,0.1108) \\ f_2^* &= (0.1645,0.6176,0.2179) \\ f_3^* &= (0.2210,0.6441,0.1349) \\ f_4^* &= (0.5637,0.3583,0.7779) \\ f_5^* &= (0.6506,0.2739,0.0756) \\ f_6^* &= (0.5287,0.3885,0.0827) \\ f_1^- &= (0.6853, 0.2364,0.0783) \\ f_2^- &= (0.5207,0.3571,0.1222) \\ f_3^- &= (0.7261,0.2276,0.0463) \\ f_4^- &= (0.2822,0.6092,0.1086) \\ f_5^- &= (0.1958,0.7229,0.0814) \\ f_6^- &= (0.1572,0.7271,0.1157) \end{aligned}$$

The values of S_i, R_i, Q_i for all alternatives are also computed and shown in Table 5.5.10.

Table 5.5.10: The values of S_i, R_i, Q_i for all alternatives

	A_1	A_2	A_3	A_4
S_i	2.4448	2.0775	2.2607	4.1651
R_i	1.0000	1.0000	0.9349	1.0000
Q_i	0.5880	0.5000	0.0439	1.0000

Step 8. The result of ranking alternatives by the values of S_i, R_i and Q_i are shown in Table 5.5.11. Based on this result, A_3 has the minimum value of Q_i (0.0439) and the two conditions discussed before are checked here. The first condition is satisfied: $Q(A_2) - Q(A_3) = 0.4561 \geq 0.3333$. Related to the second condition: the value of R_i for alternative A_3 is the minimum and the value of S_i for alternative A_2 is minimum. Therefore, alternatives A_2 and A_3 are the best choices. Thus, the most suitable health care waste treatment technologies are steam sterilization and microwave in this case study.

Table 5.5. 11: Ranking the treatment technologies (alternatives) for health care wastes dispose by the values of S_i, R_i and Q_i in increasing order

	A_1	A_2	A_3	A_4
By S_i	3	1	2	4
By R_i	2	2	1	2
By Q_i	3	2	1	4

5.6 Summary

The results obtained in this chapter are in harmony with those achieved by Dursun *et al.* (2011b) and Liu *et al.* (2013). Steam sterilization and microwave are placed in the top rankings since they appear to emit fewer pollutants and generate non-hazardous residues. “Incineration” ranks after non-incineration alternative technologies in view of the fact that the incineration of health care wastes produces particulate matters and chemical compounds that can potentially have an effect on human health and safety, and have an adverse impact on the environment. While landfill disposal is an economic alternative compared with other alternative methods, it should only be used in a limited extent because of its adverse environmental and public health effects. The construction of central steam sterilization and microwave units can be viewed as the most cost effective and the most suitable solutions from the environmental and public health point of view.

Chapter 6

6 Summary and Future Research

The present dissertation focused on a) proposing an effective optimization model for the GSCP under CO_2 emission constraints, inventory control, capacity constraints, and transportation constraints, b) presenting efficient guideline for a better quality control using adaptive control chart in the various processes involved in a supply chain network/ production system to minimize wastes and defective products, and c) evaluating the waste streams and recycling opportunities for various echelons of a supply chain. The achieved results verify that the proposed model, presented guideline, and evaluation of waste streams can enhance the GSCP significantly and provide the decision makers with various effective scenarios to decide more efficiently when they plan for their green supply chain network.

As a future research, the proposed GSCP optimization model can be extended to be applicable for supply chain networks with stochastic demands as well. In such a situation, a stochastic programming-based approach can be applied to model the planning process as it reacts to demand realizations unfolding over time. In addition, in some cases that the location of various echelons in the supply chain network needs to be selected, we can take supply chain network configuration and design decisions into account and attempt to optimize distances for transportation/logistics systems in a way that results in reduction of CO_2 emissions.

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Appendix A

A Supplementary Materials

This appendix is related to supplementary materials for Chapter 4.

A.1 The transition matrix for the in-control state

When the process is in the control state (state A), the transition matrix (P^{A}) is defined by Equation A.1-1. Here, P_{ij}^{A} refers to the probability of a transition to go from i^{th} state (previous state) to j^{th} state (current state), while the process is in the control state and the mean is on target. Please note that $i = 1$ or $j = 1$ is related to the loose control state; $i = 2$ or $j = 2$ is linked with the strict control state; and $i = 3$ or $j = 3$ is associated with the absorbing state (false alarm). The transition matrix between transient states (Q^{A}) is also shown by Equation A.1-2. The transition probabilities for the in-control duration are also demonstrated by Equations A.1-3 to A.1-6.

$$P^{\mathrm{A}} = \begin{bmatrix} P_{11}^{\mathrm{A}} & P_{12}^{\mathrm{A}} & P_{13}^{\mathrm{A}} \\ P_{21}^{\mathrm{A}} & P_{22}^{\mathrm{A}} & P_{23}^{\mathrm{A}} \\ 0 & 0 & 1 \end{bmatrix}$$

Equation A.1-1

$$Q^{\mathrm{A}} = \begin{bmatrix} P_{11}^{\mathrm{A}} & P_{12}^{\mathrm{A}} \\ P_{21}^{\mathrm{A}} & P_{22}^{\mathrm{A}} \end{bmatrix}$$

Equation A.1-2

$$P_{11}^{\mathrm{A}} = P(|Z| < W_1)e^{-\lambda h_1}$$

Equation A.1-3

$$P_{12}^{\mathrm{A}} = P(W_1 < |Z| < K_1)e^{-\lambda h_1}$$

Equation A.1-4

$$P_{21}^{\mathrm{A}} = P(|Z| < W_2)e^{-\lambda h_2}$$

Equation A.1-5

$$P_{22}^{\mathrm{A}} = P(W_2 < |Z| < K_2)e^{-\lambda h_2}$$

Equation A.1-6

A.2 The transition matrix for out-of-control state

While the process is in the out-of-control state (state B), the transition matrix (P^{B}) is defined by Equation A.2-1. Where R is the transition matrix from transient states to the absorbing state TA, 0 is a zero matrix that shows the impossibility of moving from the absorbing state to a transient state, I is an identity matrix which refers to intelligence that the system cannot leave the absorbing state when it arrives there. Here, P_{ij}^{B} is the probability of a transition to move from i^{th} state (previous state) to j^{th} state (current state), while the process is in the out-of-control state and the mean is out-of-target. Please note that, $i = 1$ or $j = 1$ is related to the loose control state; $i = 2$ or $j = 2$ is linked with the strict control state; and $i = 3$ or $j = 3$ is associated with the absorbing state (true alarm). The transition matrix between transient states (Q^{B}) is also shown by Equation A.2-2. The transition probabilities for the out-of-control duration are also demonstrated by Equations A.2-3 to A.2-5.

$$P^{\mathrm{B}} = \begin{bmatrix} \begin{bmatrix} P_{11}^{\mathrm{B}} & P_{12}^{\mathrm{B}} \\ P_{21}^{\mathrm{B}} & P_{22}^{\mathrm{B}} \end{bmatrix} & R = \begin{bmatrix} P_{13}^{\mathrm{B}} & P_{23}^{\mathrm{B}} \end{bmatrix}^{T} \\ 0 = \begin{bmatrix} 0 & 0 \end{bmatrix} & I = [1] \end{bmatrix}$$

Equation A.2-1

$$Q^{\mathrm{B}} = \begin{bmatrix} P_{11}^{\mathrm{B}} & P_{12}^{\mathrm{B}} \\ P_{21}^{\mathrm{B}} & P_{22}^{\mathrm{B}} \end{bmatrix}$$

Equation A.2-2

$$P_{i1}^{B} = P\left(-W_i - \delta\sqrt{n_i} < Z < W_i - \delta\sqrt{n_i}\right) \quad \forall\ i = 1,2$$

Equation A.2-3

$$P_{i2}^{\mathrm{B}} = P\left(W_i - \delta\sqrt{n_i} < Z < K_i - \delta\sqrt{n_i}\right) + P\left(-K_i - \delta\sqrt{n_i} < Z < -W_i - \delta\sqrt{n_i}\right) \quad \forall\ i = 1,2$$

Equation A.2-4

$$P_{i3}^{\mathrm{B}} = P\left(Z > K_i - \delta\sqrt{n_i}\right) + P(Z < -K_i - \delta\sqrt{n_i}\big) \quad \forall\ i = 1,2$$

Equation A.2-5

A.3 AATS, ANOS, and ANSS formulas

Let τ be the expected time between the l^{th} and the $(l+1)^{\text{th}}$ samples taken just prior to the occurrence of an assignable cause and the occurrence itself (DeMagalhaes *et al.* 2009; Yang *et al.* 2010). That is:

$$\tau = \frac{\int_{l.h}^{(l+1).h} \lambda e^{-\lambda t}(t - l.h)dt}{\int_{l.h}^{(l+1).h} \lambda.e^{-\lambda t}dt} = \frac{1-(1+\lambda h)}{\lambda.(1- e^{-\lambda h})}$$

Equation A.3-1

If n_i samples are taken at h_i sampling intervals and the process goes out-of-control in the sampling intervals between the l^{th} and the $(l+1)^{\text{th}}$ samples, the expected time of occurrence (τ_i) within these sampling intervals can be formulated by equation (S.13) (DeMagalhaes *et al.* 2009; Yang *et al.* 2010).

$$\tau_i = \frac{\int_{l.h}^{(l+1).h} \lambda e^{-\lambda t}(t - l.h)dt}{\int_{l.h}^{(l+1).h} \lambda.e^{-\lambda t}dt} = \frac{1-(1+\lambda.h_i).e^{-\lambda.h_i}}{\lambda.(1- e^{-\lambda.h_i})} \quad \forall\, i = 1,2$$

Equation A.3-2

To formulate the AATS, it is required to determine the average number of visits to each state of the Markov-chain, once the process is out-of-control. Based on the properties of Markov-chains, one has that the average number of visits to any transient state is:

$$[V_{LC^{\mathrm{B}}} \quad V_{SC^{\mathrm{B}}}] = V_B^T(I - Q^B)^{-1}$$

Equation A.3-3

Where:

$$V_B^T = [p_0 \quad (1 - p_0)] \text{ and } Q^B = \begin{bmatrix} P_{11}^B & P_{12}^B \\ P_{21}^B & P_{22}^B \end{bmatrix}$$

Equation A.3-4

Here, V_B^T is the vector of initial probabilities when the process is out of control. Moreover, the term of $(I - Q^B)^{-1}{}_{ij}$ that is the *ij*th component of the 2×2 matrix of $(I - Q^B)^{-1}$demonstrates the average number of visits to the *j*th transient state before absorption occurs with the assumption that the process is started in *i*th transient state. $V_{LC^{\mathrm{B}}}$ and $V_{SC^{\mathrm{B}}}$ represent the average number of visits to the related state when the mean is out-of-control. The equations for the AATS, ANOS, and ANSS are formulated, respectively by Equations A.3-5: (S-18) (DeMagalhaes *et al.* 2009).

$$AATS = h_1 . V_{LC^{\mathrm{B}}} + h_2 . V_{SC^{\mathrm{B}}} + (h_1 - \tau_1^B) . p_0 + (h_2 - \tau_2^B) . (1 - p_0)$$

Equation A.3-5

$$ANOS = n_1 . V_{LC^{\mathrm{B}}} + n_2 . V_{SC^{\mathrm{B}}}$$

Equation A.3-6

$$ANSS = V_{LC^{\mathrm{B}}} + V_{SC^{\mathrm{B}}}$$

Equation A.3-7

A.4 Achieved Results

Table A.4.1: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSC model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSC** Model	Optimum AATS	133.65944	33.90079	11.26107	4.99532	2.88767	2.06650	1.57585	1.50483	1.50011
	% IM	-0.38	-1.50	-4.65	-11.12	-20.94	-31.92	-46.48	-49.76	-50.00
	ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	W_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	W_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00
	K_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	K_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00
Minimizing **ANOS** for the **VSC** Model	AATS	133.65944	33.90079	11.26107	4.99532	2.88767	2.06650	1.57585	1.50483	1.50011
	% IM	-0.38	-1.50	-4.65	-11.12	-20.94	-31.92	-46.48	-49.76	-50.00
	Optimum ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	W_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	W_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00
	K_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	K_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00
Minimizing **ANSS** for the **VSC** Model	AATS	133.65944	33.90079	11.26107	4.99532	2.88767	2.06650	1.57585	1.50483	1.50011
	% IM	-0.38	-1.50	-4.65	-11.12	-20.94	-31.92	-46.48	-49.76	-50.00
	ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Optimum ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	W_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	W_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00
	K_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
	K_2	3.60	3.60	5.40	5.40	5.40	5.40	5.90	6.00	6.00

Table A.4.2: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSI model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSI** Model	Optimum AATS	116.31792	20.13565	4.42348	1.95566	1.57308	1.51332	1.50087	1.50006	1.50001
	% IM	12.65	39.72	58.89	56.50	34.12	3.39	-39.51	-49.29	-49.99
	ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	h_1	3.00	3.00	3.00	3.00	3.00	3.00	3.00	1.50	1.10
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	W	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.96	1.67
Minimizing **ANOS** for the **VSI** Model	AATS	116.79478	29.35838	6.51676	2.62867	1.80510	1.53607	1.50863	1.50338	1.50002
	% IM	12.29	12.10	39.44	41.52	24.40	1.94	-40.23	-49.62	-49.99
	Optimum ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	h_1	2.80	1.20	1.20	1.20	1.20	2.70	1.10	1.10	1.20
	h_2	0.03	0.60	0.03	0.04	0.08	0.05	0.08	0.70	0.07
	W	0.45	0.96	1.36	1.36	1.34	0.46	1.64	1.15	1.34
Minimizing **ANSS** for the **VSI** Model	AATS	116.79478	29.35838	6.51676	2.62867	1.80510	1.54629	1.50378	1.50020	1.50004
	% IM	12.29	12.10	39.44	41.52	24.40	1.29	-39.78	-49.30	-49.99
	ANOS	665.79716	167.00390	53.80532	22.47656	11.93832	7.83246	5.37919	5.02410	5.00052
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Optimum ANSS	133.15943	33.40078	10.76106	4.49531	2.38766	1.56649	1.07584	1.00482	1.00010
	% IM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	h_1	2.80	1.20	1.20	1.20	1.20	1.50	1.10	1.10	1.10
	h_2	0.03	0.60	0.03	0.04	0.08	0.05	0.01	0.03	0.30
	W	0.45	0.96	1.36	1.36	1.34	0.94	1.67	1.67	1.52

Table A.4. 3: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSIC model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSIC** Model	Optimum AATS	113.63549	18.73685	4.14595	1.92384	1.57081	1.51319	1.50087	1.50007	1.50001
	% IM	14.66	43.90	61.47	57.20	34.21	3.40	-39.51	-49.29	-49.99
	ANOS	633.42691	149.58542	48.75759	20.95857	11.61809	7.78865	5.38393	5.02610	5.00071
	% IM	4.86	10.43	9.38	6.75	2.68	0.56	-0.09	-0.04	0.00
	ANSS	126.68538	29.91708	9.75152	4.19171	2.32362	1.55773	1.07679	1.00522	1.00014
	% IM	4.86	10.43	9.38	6.75	2.68	0.56	-0.09	-0.04	0.00
	h_1	1.60	2.20	3.00	3.00	3.00	3.00	3.00	1.70	1.10
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	W_1	0.88	0.60	0.43	0.43	0.43	0.43	0.43	0.81	1.68
	W_2	0.88	0.60	0.43	0.43	0.43	0.43	0.43	0.81	1.64
	K_1	3.30	3.50	3.70	3.50	3.30	3.10	3.10	3.10	3.10
	K_2	2.77	2.84	2.88	2.89	2.91	2.96	2.96	2.90	2.57
Minimizing **ANOS** for the **VSIC** Model	AATS	115.11888	20.64126	5.54867	2.56422	1.79992	1.57970	1.56836	1.50436	1.50010
	% IM	13. 55	38.20	48.44	42.96	24.62	-0.84	-45.79	-49.72	-50.00
	Optimum ANOS	604.03404	123.43849	37.52074	17.22132	10.47378	7.52024	5.37972	5.02419	5.00053
	% IM	9.28	26.09	30.27	23.38	12.27	3.99	-0.01	0.00	0.00
	ANSS	120.80681	24.68770	7.50415	3.44426	2.09476	1.50405	1.07594	1.00484	1.00011
	% IM	9.28	26.09	30.27	23.38	12.27	3.99	-0.01	0.00	0.00
	h_1	1.10	1.10	1.10	1.10	1.10	1.10	3.00	3.00	3.00
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.90	0.90	0.90
	W_1	1.68	1.68	1.68	1.68	1.68	1.68	0.06	0.06	0.06
	W_2	1.60	1.59	1.59	1.60	1.62	1.64	0.06	0.06	0.06
	K_1	3.30	3.40	3.40	3.30	3.20	3.10	3.10	3.10	3.10
	K_2	2.33	2.28	2.28	2.33	2.41	2.57	3.00	3.00	3.00
Minimizing **ANSS** for the **VSIC** Model	AATS	115.11888	20.64126	5.54867	2.56422	1.79992	1.57970	1.56836	1.50436	1.50010
	% IM	13.55	38.20	48.44	42.96	24.62	-0.84	-45.79	-49.72	-50.00
	ANOS	604.03404	123.43849	37.52074	17.22132	10.47378	7.52024	5.37972	5.02419	5.00053
	% IM	9.28	26.09	30.27	23.38	12.27	3.99	-0.01	0.00	0.00
	Optimum ANSS	120.80681	24.68770	7.50415	3.44426	2.09476	1.50405	1.07594	1.00484	1.00011
	% IM	9.28	26.09	30.27	23.38	12.27	3.99	-0.01	0.00	0.00
	h_1	1.10	1.10	1.10	1.10	1.10	1.10	3.00	3.00	3.00
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.90	0.90	0.90
	W_1	1.68	1.68	1.68	1.68	1.68	1.68	0.06	0.06	0.06
	W_2	1.60	1.59	1.59	1.60	1.62	1.64	0.06	0.06	0.06
	K_1	3.30	3.40	3.40	3.30	3.20	3.10	3.10	3.10	3.10
	K_2	2.33	2.28	2.28	2.33	2.41	2.57	3.00	3.00	3.00

Table A.4.4: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSS model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSS** Model	Optimum AATS	75.54977	8.80913	4.22246	2.88266	2.29413	1.95955	1.59654	1.51184	1.50069
	% IM	43.26	73.63	60.76	35.87	3.92	-25.09	-48.40	-50.46	-50.05
	ANOS	518.61770	78.60572	35.22012	19.99309	13.13184	8.95720	5.57871	5.07099	5.00407
	% IM	22.11	52.93	34.54	11.05	-10.00	-14.36	-3.71	-0.93	-0.07
	ANSS	75.04976	8.30912	3.72245	2.38266	1.79412	1.45954	1.09653	1.01183	1.00068
	% IM	43.64	75.12	65.41	47.00	24.86	6.83	-1.92	-0.70	-0.06
	n_1	1	1	3	3	4	4	4	4	4
	n_2	30	30	21	15	12	9	6	6	6
	W	1.47	1.47	1.58	1.38	1.52	1.28	0.67	0.67	0.67
Minimizing **ANOS** for the **VSS** Model	AATS	75.54977	8.80913	4.44528	3.08690	2.48555	2.00222	1.59654	1.51184	1.50069
	% IM	43.26	73.63	58.69	31.33	-4.10	-27.81	-48.40	-50.46	-50.05
	Optimum ANOS	518.61770	78.60572	32.78648	18.23341	11.49781	8.00065	5.57871	5.07099	5.00407
	% IM	22.11	52.93	39.06	18.88	3.69	-2.15	-3.71	-0.93	-0.07
	ANSS	75.04976	8.30912	3.94527	2.58689	1.98554	1.50221	1.09653	1.01183	1.00068
	% IM	43.64	75.12	63.34	42.45	16.84	4.10	-1.92	-0.70	-0.06
	n_1	1	1	1	1	1	4	4	4	4
	n_2	30	30	19	11	7	6	6	6	6
	W	1.47	1.47	1.22	0.84	0.43	0.67	0.67	0.67	0.67
Minimizing **ANSS** for the **VSS** Model	AATS	75.54977	8.80913	4.22246	2.88266	2.29413	1.95955	1.59654	1.51184	1.50069
	% IM	43.26	73.63	60.76	35.87	3.92	-25.09	-48.40	-50.46	-50.05
	ANOS	518.61770	78.60572	35.22012	19.99309	13.13184	8.95720	5.57871	5.07099	5.00407
	% IM	22.11	52.93	34.54	11.05	-10.00	-14.36	-3.71	-0.93	-0.07
	Optimum ANSS	75.04976	8.30912	3.72245	2.38266	1.79412	1.45954	1.09653	1.01183	1.00068
	% IM	43.64	75.12	65.41	47.00	24.86	6.83	-1.92	-0.70	-0.06
	n_1	1	1	3	3	4	4	4	4	4
	n_2	30	30	21	15	12	9	6	6	6
	W	1.47	1.47	1.58	1.38	1.52	1.28	0.67	0.67	0.67

Table A.4.5: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSSC model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSSC** Model	Optimum AATS	32.85306	7.21824	3.85500	2.79906	2.28905	1.97121	1.60669	1.51472	1.50094
	% IM	75.33	78.39	64.18	37.73	4.131	-25.84	-49.35	-50.75	-50.08
	ANOS	205.64350	51.65814	26.89955	17.89733	12.11030	8.66797	5.63964	5.08826	5.00561
	% IM	69.11	69.07	50.01	20.37	-1.44	-10.67	-4.84	-1.28	-0.10
	ANSS	32.35305	6.71823	3.35499	2.29905	1.78905	1.47120	1.10668	1.01471	1.00094
	% IM	75.70	79.89	68.82	48.86	25.07	6.08	-2.87	-0.98	-0.08
	n_1	1	1	2	3	4	4	4	4	4
	n_2	30	24	16	13	10	8	6	6	6
	W_1	1.48	1.36	1.24	1.28	1.38	1.15	0.67	0.67	0.67
	W_2	1.42	1.32	1.22	1.26	1.37	1.14	0.67	0.67	0.67
	K_1	6.00	6.00	4.30	3.30	3.10	3.10	3.10	3.10	3.10
	K_2	2.33	2.42	2.50	2.59	2.72	2.81	2.92	2.92	2.92
Minimizing **ANOS** for the **VSSC** Model	AATS	32.85306	7.30668	3.97684	2.90867	2.39825	1.99770	1.60669	1.51472	1.50094
	% IM	75.33	78.12	63.04	35.29	-0.44	-27.53	-49.35	-50.75	-50.08
	Optimum ANOS	205.64350	50.9195 2	26.00355	15.99908	10.88660	7.97352	5.63964	5.08826	5.00561
	% IM	69.11	69.51	51.67	28.82	8.81	-1.80	-4.84	-1.28	-0.10
	ANSS	32.35305	6.80667	3.47683	2.40866	1.89824	1.49769	1.10668	1.01471	1.00094
	% IM	75.70	79.62	67.69	46.42	20.50	4.39	-2.87	-0.98	-0.08
	n_1	1	1	1	1	1	4	4	4	4
	n_2	30	28	15	10	7	6	6	6	6
	W_1	1.48	1.45	1.07	0.76	0.43	0.67	0.67	0.67	0.67
	W_2	1.42	1.39	1.05	0.76	0.43	0.67	0.67	0.67	0.67
	K_1	6.00	6.00	5.80	4.90	4.40	3.10	3.10	3.10	3.10
	K_2	2.33	2.36	2.60	2.74	2.87	2.92	2.92	2.92	2.92
Minimizing **ANSS** for the **VSSC** Model	AATS	32.85306	7.21824	3.85500	2.79906	2.28905	1.97121	1.60669	1.51472	1.50094
	% IM	75.33	78.39	64.18	37.73	4.13	-25.84	-49.35	-50.75	-50.08
	ANOS	205.64350	51.6581	26.89955	17.89733	12.11030	8.66797	5.63964	5.08826	5.00561
	% IM	69.11	69.07	50.01	20.37	-1.44	-10.67	-4.84	-1.28	-0.10
	Optimum ANSS	32.35305	6.71823	3.35499	2.29905	1.78905	1.47120	1.10668	1.01471	1.00094
	% IM	75.70	79.89	68.82	48.86	25.07	6.08	-2.87	-0.98	-0.08
	n_1	1	1	2	3	4	4	4	4	4
	n_2	30	24	16	13	10	8	6	6	6
	W_1	1.48	1.36	1.24	1.28	1.38	1.15	0.67	0.67	0.67
	W_2	1.42	1.32	1.22	1.26	1.37	1.14	0.67	0.67	0.67
	K_1	6.00	6.00	4.30	3.30	3.10	3.10	3.10	3.10	3.10
	K_2	2.33	2.42	2.50	2.59	2.72	2.81	2.92	2.92	2.92

Table A.4.6: The obtained values of design parameters, performance measures, and %IM at achieved minimum AATS, ANOS, and ANSS for the VSSI model

	δ	0.25	0.50	0.75	1.00	1.25	1.50	2.00	2.50	3.00
Minimizing **AATS** for the **VSSI** Model	Optimum AATS	69.87237	7.25176	2.84609	1.81962	1.57067	1.51754	1.50143	1.50014	1.50002
	% IM	47.53	78.29	73.55	59.52	34.22	3.13	-39.56	-49.30	-49.99
	ANOS	518.61770	82.46233	37.79387	20.02113	11.68018	8.00065	5.57871	5.07099	5.00630
	% IM	22.11	50.62	29.76	10.93	2.16	-2.15	-3.71	-0.93	-0.12
	ANSS	75.04976	8.60981	4.70250	3.23167	2.12337	1.50221	1.09653	1.01183	1.00090
	% IM	43.64	74.22	56.30	28.11	11.07	4.10	-1.92	-0.70	-0.08
	h_1	1.16	1.19	1.50	1.99	2.98	1.99	1.99	1.99	1.50
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	2	3	3	4	4	4	4
	n_2	30	26	11	7	6	6	6	6	7
	W	1.47	1.40	0.96	0.67	0.43	0.67	0.67	0.67	0.96
Minimizing **ANOS** for the **VSSI** Model	AATS	69.87237	7.34155	3.52175	2.21258	1.70836	1.51754	1.50143	1.50014	1.50002
	% IM	47.53	78.02	67.27	50.78	28.45	3.13	-39.56	-49.30	-49.99
	Optimum ANOS	518.61770	78.60572	32.78648	18.23341	11.49781	8.00065	5.57871	5.07099	5.00407
	% IM	22.11	52.93	39.07	18.88	3.69	-2.15	-3.71	-0.93	-0.07
	ANSS	75.04976	8.309123	3.94528	2.58689	1.98554	1.50221	1.09653	1.01183	1.00068
	% IM	43.64	75.12	63.39	42.45	16.84	4.10	-1.92	-0.70	-0.06
	h_1	1.16	1.16	1.28	1.66	2.98	1.99	1.99	1.99	1.99
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	1	1	1	4	4	4	4
	n_2	30	30	19	11	7	6	6	6	6
	W	1.47	1.47	1.22	0.84	0.43	0.67	0.67	0.67	0.67
Minimizing **ANSS** for the **VSSI** Model	AATS	69.87237	7.34155	3.19485	2.08276	1.70561	1.54883	1.50143	1.50014	1.50002
	% IM	47.53	78.02	70.31	53.67	28.57	1.13	-39.56	-49.30	-49.99
	ANOS	518.61770	78.60572	35.22012	19.99309	13.13184	8.95720	5.57871	5.07099	5.00407
	% IM	22.11	52.93	34.54	11.05	-10.00	-14.36	-3.71	-0.93	-0.07
	Optimum ANSS	75.04976	8.30912	3.72245	2.38266	1.79412	1.45954	1.09653	1.01183	1.00068
	% IM	43.64	75.12	65.41	47.00	24.86	6.83	-1.92	-0.70	-0.06
	h_1	1.16	1.16	1.12	1.20	1.14	1.25	1.99	1.99	1.99
	h_2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	n_1	1	1	3	3	4	4	4	4	4
	n_2	30	30	21	15	12	9	6	6	6
	W	1.47	1.47	1.58	1.38	1.52	1.28	0.67	0.67	0.67