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Development of a Decision Support Framework for Sustainable and Resilient Supplier Selection and Order Allocation

by

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Development of a Decision Support Framework for Sustainable and Resilient Supplier Selection and Order Allocation

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CERTIFICATE OF APPROVAL

This is to certify that the research work presented in the dissertation, entitled **"Development of a Decision Support Framework for Sustainable and Resilient Supplier Selection and Order Allocation"** was conducted under the supervision of **Dr. Salman Sagheer Warsi**. No part of this dissertation has been submitted anywhere else for any other degree. This dissertation is submitted to the **Department of Mechanical Engineering, Capital University of Science and Technology** in partial fulfillment of the requirements for the degree of Doctor in Philosophy in the field of **Mechanical Engineering**. The open defence of the dissertation was conducted on **December 08, 2023**.

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List of Publications

It is certified that following publication(s) have been made out of the research work that has been carried out for this dissertation:-

1. **S. A. Kayani**, S. S. Warsi, and R. A. Liaqait, “A smart decision support framework for sustainable and resilient supplier selection and order allocation in the pharmaceutical industry,” *Sustainability*, vol. 15, no. 7, 5962, 2023.

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Abstract

Supplier selection and order allocation (SS-OA) are two of the most important strategic decisions for supply chain network design and operation. If sustainability and resilience criteria are taken into consideration together and a holistic sustainable and resilient SS-OA is carried out, it may enable the supply chain network to perform better when subjected to disruption scenarios. In order to achieve this objective, a novel comprehensive multi-phase, multi-period sustainable and resilient SS-OA decision support framework has been proposed. This framework combines multi-criteria decision making techniques with multi-objective programming while taking into account triple bottom line (TBL) sustainability and resilience criteria simultaneously for optimizing a multi-modal, multi-echelon supply chain network susceptible to disruption risks.

The proposed decision support framework has been divided into 5 phases. In the first phase, multi-criteria decision-making (MCDM) techniques fuzzy extended Analytic Hierarchy Process (FE-AHP) and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) have been used to evaluate the potential suppliers in the context of TBL sustainability and resilience criteria. A multi-objective, mixed-integer nonlinear programming (MOMINLP) mathematical model has been developed in the second phase for optimal order allocation to the selected suppliers. The model has been fuzzified to incorporate real-world uncertainty and solved by using a nonlinear solver and an exact algorithm i.e. Augmented ε-Constraint 2 (AUGMECON2) method simultaneously for generating Pareto optimal solutions. TOPSIS augmented with objective functions weights determined using Criteria Importance through Intercriteria Correlation (CRITIC) method has been applied in the third phase to rank and select the best solutions. In the fourth phase, the MOMINLP mathematical model has been reconsidered and optimized with respect to supply chain network service level while taking into account the impact of multiple random and intentional disruption scenarios. In order to arrive at the best performance configuration for the supply chain network, the influence of the disruption scenarios on the service level of the network has been evaluated and the ideal, no disruption and disruption solutions have

been compared against fixed criteria in the fifth and the last phase of the decision support framework.

The effectiveness of the decision support framework has been demonstrated by implementing an application case study based on data collected from the pharmaceutical industry. The results indicate that among the TBL sustainability criteria considered, product price, past business, innovative capability, and information disclosure rank as the most significant sub-criteria for the decision makers (DMs) in the pharmaceutical industry while robustness and flexibility are considered the most valued attributes for potential suppliers as far as the resilience criterion is concerned. Furthermore, transfer cost and custom clearance cost together comprise more than two-thirds of the overall cost of the supply chain network. It has also been noted that inland transportation of goods is dominated by rail as the most preferred mode of transport. The comparison and analysis of the no disruption and disruption solutions indicates that the proposed decision support framework enables the supply chain network to achieve the DMs' specified performance target. However, in order to maintain the desired service level and to counter the possibility of a stock-out under the influence of probabilistic and network disruptions, the DMs have to allocate greater financial resources e.g. a 19.2% raise in the total cost for supplier-2 becoming unavailable, and be willing to accept a substantial rise in the value of the transportation time (a maximum of 42.3% for a substitute supplier replacing supplier-2) along with a considerable increase in environmental impact.

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Abbreviations

ANFIS	Adaptive Neuro FIS
ANP	Analytic Network Process
AQL	Acceptable Quality Limit
ARAS	Additive Ratio Assessment
AUGMECON	Augmented ε-Constraint
AUGMECON2	Augmented ε-Constraint 2
AUGMECON-Py	Python Framework for Augmented ε-Constraint
AUGMECON-R	Robust Augmented ε-Constraint
BIM	Building Information Modeling
BWM	Best Worst Method
CC	Closeness Coefficient
CCR Model	Charnes, Cooper, Rhodes Model
CRITIC	Criteria Importance through Intercriteria Correlation
DA	Discriminant Analysis
DEA	Data Envelopment Analysis
DEMATEL	Decision Making Trial and Evaluation Laboratory
DFT	Decision Field Theory
DM	Decision Maker
EC	Economic Criteria
EI	Environmental Impact
$\mathbf{E_nC}$	Environment Criteria
EOQ	Economic Order Quantity
FE-AHP	Fuzzy Extended Analytic Hierarchy Process
FIS	Fuzzy Inference System
FMOMINLP	Fuzzy Multi-objective Mixed-integer Nonlinear Programming

FST	Fuzzy Set Theory
FTOPSIS	Fuzzy Technique for Order of Preference by Similarity to Ideal Solution
GA	Genetic Algorithm
GP	Goal Programming
GRA	Grey Relational Analysis
LCL	Less than Container Load
LEWM	Language Entropy Weight Method
MCDM	Multi-criteria Decision Making
MCGDM	Multi-criteria Group Decision Making
MILP	Mixed-integer Linear Programming
MINLP	Mixed-integer Nonlinear Programming
MIP	Mixed-integer Programming
MOILP	Multi-objective Integer Linear Programming
MOLP	Multi-objective Linear Programming
MONLP	Multi-objective Nonlinear Programming
MOP	Multi-objective Programming
OPA	Ordinal Priority Approach
PIPRECIA	Pivot Pairwise Relative Criteria Importance Assessment
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
QFD	Quality Function Deployment
RC	Resilience Criteria
RFI	Request for Information
RFP	Request for Proposal
RFQ	Request for Quotation
SC	Social Criteria
SCI	Supply Chain Index
SRSS-OA	Sustainable and Resilient Supplier Selection and Order Allocation
SS-OA	Supplier Selection and Order Allocation
SSS-OA	Sustainable Supplier Selection and Order Allocation

TBL	Triple Bottom Line
TC	Total Cost
TEU	Twenty-foot Equivalent Unit
TFN	Triangular Fuzzy Number
TODIM	Tomada de Decisao Interativa Multicriterio
TTT	Total Travel Time
TVSP	Total Value of Sustainable Purchasing
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment
WSM	Weighted Sum Model

Symbols

t	Time period
ϕ	Confidence value
S	Slack variable
r	Range of objective function
ε	Right-hand side value of objective function
α_R	Risk threshold
R_s	Risk expectation value of supplier
w_i^{Risk}	Normalized risk weight
Q	Order quantity
M	Replenishment level
H	Inventory on hand at the review period
μ	Mean value of demand

Chapter 1

Introduction

1.1 Research Background

Sustainability can be defined as creating and maintaining conditions under which humans and nature co-exist in productive harmony thus ensuring future of present and coming generations. Sustainable manufacturing refers to the development of manufactured products through processes that are economically sound, have minimal environmental impact, and are firmly based on the principles of energy and natural resource conservation. It essentially includes employee, community, and product safety, and leads to a positive societal impact. Supply chain management is a vital component of any manufacturing operation, thus, supply chain sustainability may be defined as the management of supply chains where all the three dimensions or aspects of sustainability i.e. economic (or profit), environmental (or planet), and social (or people), the so called "triple bottom line" or TBL, are taken into consideration [1].

Sustainable supply chain management aims for voluntary integration of the three dimensions of sustainability as referred to above with key inter-organizational business systems designed for effective and efficient management of material, information, and capital flows associated with the procurement, production, and distribution of products [2]. The primary objective of this integration is to achieve an optimal combination of the three dimensions of sustainability with supply chain network operations. There is considerable practical evidence around the world and reported in literature that sustainable supply chains usually offer superior logistics performance and resources utilization [3]. Thus, sustainability and adherence to sustainability practices usually serves as a source of competitive advantage for any organization engaged in international business or trade.

Supplier selection is the process by which firms identify, evaluate, and contract with suppliers. The main objective of the supplier selection process is to reduce purchase risk, maximize overall value to the purchaser, and develop long term relationships between buyers and suppliers [4]. Supplier selection is divided into two main categories: single sourcing, where only one supplier is able to fulfill an organization's demands, and multiple sourcing, where more than one supplier is selected as no one supplier is single-handedly capable of meeting the demand requirements of the enterprise. In case of single sourcing, the decision makers (DMs) have to choose and select only one supplier where as in the case of multiple sourcing the task of the DMs is more challenging as they have to select best suppliers out of many and then allocate optimal quantities to each supplier in order to create an environment of fair play and genuine competition, while maximizing returns for their own organization at the same time. Usually the practice of multiple sourcing is preferred due to its inherent characteristics of ensuring order flexibility, capacity, and timely delivery given the variation that may exist in the orders that can be placed by any organization [5].

Supplier selection is a complex phenomenon and a multi-criteria decision making (MCDM) process that requires assessment and evaluation of various conflicting criteria i.e. cost, product quality, delivery time, volume flexibility etc. that need to be taken into consideration in order to select consistent suppliers [6, 7]. Supplier selection and order allocation (SS-OA) has been traditionally carried out using economic or the so called conventional criteria only but lately, the growing concern for sustainability issues in manufacturing and supply chain management has shifted the focus towards inclusion of environmental and social criteria in this process as well. This integration of TBL sustainability criteria with supplier selection and order allocation leads to adding more complexity to the SS-OA problem [8]. In sustainable supplier selection and order allocation (SSS-OA), suppliers are selected using TBL sustainability criteria whereas order allocation is carried out using multiple sourcing strategy.

International supply chains are vulnerable to disruptions. In recent years, the most important among these disruptions has been the outbreak and spread of the COVID-19 pandemic, which lead to restrictions on goods movement, border closures, and reduced workforce availability at an unprecedented scale. The impact of the pandemic caused the world economy to contract by 3.5% in 2020[1] with massive loss to global value chain. Natural or manmade accidents can impact transportation infrastructure, warehouses, and distribution centers. Congestion or blockage of transportation routes where ships, trains, and trucks are queued up to unload or load cargo can delay shipments leading to logistic bottlenecks. The Suez Canal obstruction in 2021 or the ongoing Panama Canal crisis due to extreme drought conditions is an example of this category of disruptions. The weeklong 2021 Suez Canal obstruction held up $9 billion in global trade each day of the blockage[2]. The nature and extent of global supply chain disruptions and the magnitude of their fiscal and logistic impact entails a detailed evaluation of supply chain network performance in terms of resilience.

Resilience is defined as the intrinsic ability of an organization, system, or network to keep or recover a steady state, thereby allowing it to continue normal operations after facing a disruptive event [9]. Supply chain resilience may be referred to as the ability of a supply chain network to both resist disruptions and to recover operational capability after disruptions have occurred. Disruptions are random events that cause a supply chain network to stop functioning either completely or partially for any period of time.

Disruptions are not rare events; given the large number of disruption causes and the vast scale of modern supply chains, the likelihood of the supply chain network being disrupted owing to one reason or another in a given time period is quite high. Certain major natural or manmade (intentional or unintentional) disruptions i.e. earthquakes, floods, pandemics, territorial conflicts, and industrial accidents happen quite infrequently but various minor disruptions i.e. power outages, road

[1] https://www.brookings.edu/

[2] https://porteconomicsmanagement.org/

blocks, machine breakdowns etc. occurring along the supply chain network are fairly common. Whether major or minor, a disruption can lead to a domino effect through the supply chain network undermining its performance unless there are measures in place to check or counter the cascading effect of the disruption. In extant literature, disruptions and their impact is usually discussed as part of the supply uncertainty. More specifically, disruptions are treated as special cases of yield, capacity, and lead time uncertainty. Due to the differences between modeling approaches and the managerial insights gained, in the following chapters, disruptions and the evaluation of their impact is limited to random demand in order time intervals (leading to probabilistic disruptions), and supplier unavailability, inaccessible facilities, and lost storage capacity (all leading to network disruptions), which may cause a detrimental effect on the supply chain network service level [10].

Service level is the supply chain network performance target specified by the DMs. It is a quantitative measure that identifies inventory performance objectives with the aim to ensure that all customer orders are fulfilled within acceptable limits of the performance target. Service level is often measured in terms of an order cycle time, case fill rate, line fill rate, order fill rate, or any combination of these. All organizations, manufacturing or otherwise, employ suitable demand forecasting techniques for estimating order quantities during inventory replenishment cycle for any given time period. At this stage, demand uncertainty must be taken into consideration in order to protect against a stock-out situation in which demand exceeds forecast. This requirement that the probability of inventory on hand should not fall below a certain critical level by the end of a review period has been referred to as α service level by Chen and Krass [11]. This type of service level is consequential when the DMs are more concerned with the likelihood of a stock-out occurring rather than by its magnitude. A countermeasure employed in practice for avoiding the possibility of a stock-out is the addition of safety stock to the base inventory. In this approach the objective is to determine an inventory replenishment level that will meet a desired performance level such as a low probability of stock-out for any time period considered. In this situation, safety stock will act as a buffer to absorb any higher than usual demand during the review period plus the demand during the lead time period. It may be concluded that achieving a target service level can be considered a reliable indicator for a supply chain network to be regarded as resilient against probabilistic or network disruptions.

1.2 Research Motivation

In light of the discussion presented in the previous section, it is evident that incorporating sustainability in supply chain network operations offers a strategic advantage to any organization in terms of resource consumption, logistic performance, and long-term value creation. However, a sustainable supply chain though efficient would always be vulnerable to unexpected natural or manmade disasters. Selecting suppliers that have been evaluated and allocating optimal order quantities that have been determined based on a criteria that incorporates both TBL sustainability dimensions and resilience aspects concurrently would not only ensure an adequately performing sustainable supply chain but will also significantly reduce the likelihood of disruptions propagating through the network and service level degradation when the supply chain is disrupted [12].

1.3 Problem Statement

Modern supply chains extend beyond international borders, operate in diverse economic, environmental, and social settings, and are subject to influence from multiple types of natural or manmade disruptions. The state of the art literature lacks an integrated methodology that combines TBL sustainability and resilience criteria concurrently in both supplier selection and order allocation parts of the SS-OA problem while taking into account the impact of demand uncertainty and network disruptions.

The integrated methodology should offer a step by step procedure to select suppliers and to carry out order allocation based on a simultaneous consideration of

TBL sustainability and resilience criteria, and provide a means to evaluate supply chain network performance under the influence of multiple disruption scenarios.

1.4 Research Objectives

The principal objectives of the research work presented in this thesis are summarized as follows:

(a) Development of an integrated methodology and a holistic multi-phase, multi-period decision support framework for sustainable and resilient supplier selection and order allocation (SRSS-OA) problem.

(b) Evaluation of the effectiveness of the proposed decision support framework by conducting multi-criteria optimization of a real-life complex supply chain network subject to disruption risks.

(c) Comparison of the ideal, no disruption and disruption solutions and identification of the best performance configuration for the supply chain network considered.

A graphical abstract that highlights the key elements of the research work presented in this thesis has been included in Fig. 1.1.

1.5 Research Contribution

A novel holistic multi-phase, multi-period sustainable and resilient SS-OA decision support framework has been proposed in this research thesis. The proposed framework combines fuzzy MCDM techniques with fuzzy multi-objective mixed-integer nonlinear programming (FMOMINLP) mathematical model to optimize TBL sustainability and resilience criteria concurrently for a multi-modal, multi-echelon supply chain network. The efficacy of the decision support framework has

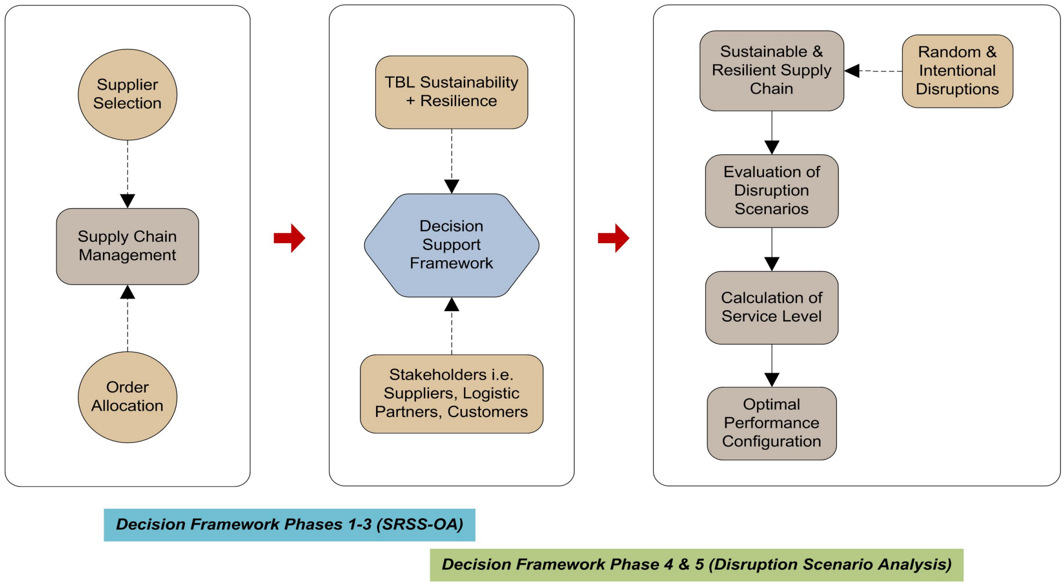


FIGURE 1.1: Graphical abstract

been demonstrated by implementing it using data from the pharmaceutical industry, which has emerged as one of the most critical industry sectors considering the impact of the COVID-19 pandemic globally [13].

The decision support framework has been implemented in 2 parts i.e. in the first part comprising of phases 1-3, sustainable and resilient SS-OA has been carried out, which is followed by disruption scenario evaluation and comparison of no disruption and disruption solutions in the second part consisting of phase 4 and phase 5, respectively. A conceptual diagram that illustrates the implementation of the proposed decision support framework on the supply chain network considered in this research work has been included in Fig. 1.2.

The research work included in the following chapters presents a unique perspective on supplier selection and order allocation. The proposed decision support framework is inclined towards the concept of Industry 5.0 and aligned with its core values i.e. sustainability and resilience [14].

It considers and analyzes SRSS-OA problem with an aim to deliver value added service to customers by attempting to minimize supply chain vulnerability against natural or manmade disruptions. Sustainable and resilient supply chain networks can in turn ensure public well being in times of turmoil and serve to achieve the fundamental objectives of the Industry 5.0 paradigm i.e. societal heterogeneity, environmental and social value, and human-centric technological transformation.

1.6 Thesis Outline

The rest of the thesis has been organized as follows:

Chapter 2

In this chapter, a detailed and contextual overview and comparison of the sustainable and resilient SS-OA literature with reference to supply chain network disruptions and service level has been presented.

Chapter 3

This chapter introduces the structure and components of the problem that has been addressed in this research work and presents the complete integrated methodology i.e. the decision support framework, the mathematical model, and the solution approach.

Chapter 4

In this chapter, an application case study has been used to implement and demonstrate the SRSS-OA part of the decision support framework (represented by phases 1-3) as included in chapter 3.

Chapter 5

This chapter presents a detailed analysis in order to evaluate the performance of the supply chain network under the influence of multiple disruption scenarios using the procedure outlined in phase 4 and phase 5 of the proposed decision support framework as included in chapter 3.

Chapter 6

This chapter concludes the preceding research work and suggests potential research avenues.

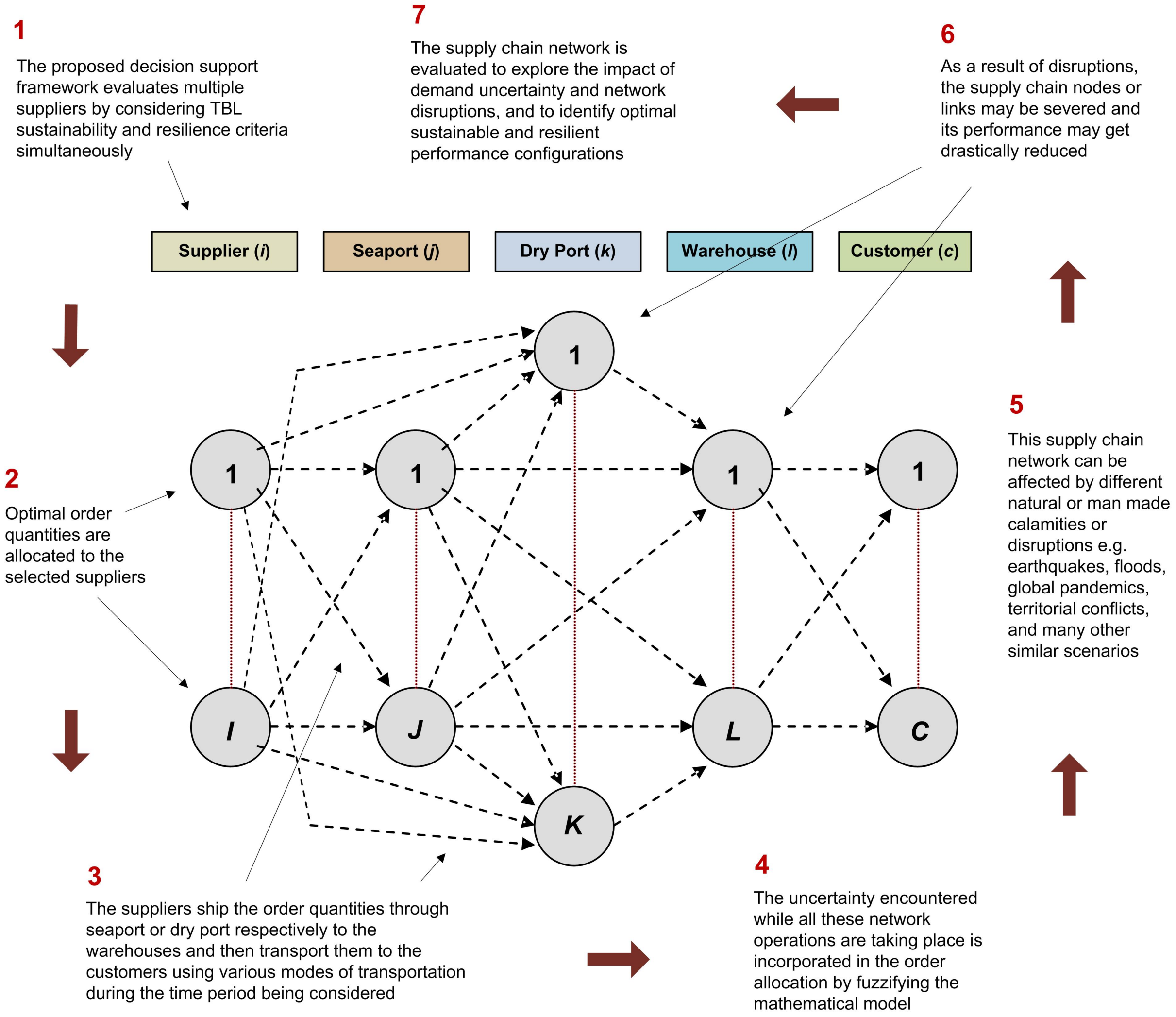


FIGURE 1.2: A conceptual diagram for implementation of the proposed decision support framework

Chapter 2

Literature Review

Supplier selection and order allocation are generally paired together and treated as complementary activities. For a DM, supplier selection is usually the first step in addressing a SS-OA problem. Hence, identifying the right criteria for evaluating suppliers should be considered a key issue with far-reaching implications in supply chain management.

2.1 Supplier Selection Criteria

Supplier selection is a well established research area and a diverse body of knowledge exists that covers different aspects of this field of study. Various review publications have systematically analyzed the progress and development of supplier selection concepts and techniques in general and the evolution of supplier selection criteria in particular over the years i.e. de Boer et al. [15] (methods), Bhutta [16] (methodologies), Wu and Barnes [17] (decision making models and approaches), Ware et al. [18] (criteria, methodologies, and application case studies), Wetzstein et al. [19] (methodologies), Simic et al. [20] (integration of Fuzzy Set Theory (FST) with supplier evaluation techniques), Ocampo et al. [21] (methods and techniques), Aouadni et al. (MCDM techniques and mathematical models for SS-OA, and application case studies) [22], and Naqvi and Amin [23] (application of operations research techniques for SS-OA).

2.1.1 The Advent of Conventional Criteria (1966-1999)

The earliest reported criteria for supplier evaluation by Dickson comprised of 23 different attributes [24]. This research work identifies cost, delivery rate, quality, and supplier efficacy etc. as important criteria for single supplier selection. The research study aims to examine the various approaches and factors involved in the vendor selection process and offers insights into the decision making aspects. The author highlights the significance of vendor selection in achieving supply chain efficiency and effectiveness. The research work recognizes that selecting the right vendors is crucial for ensuring product quality, timely delivery, cost-effectiveness, and overall customer satisfaction. The research study has reviewed different vendor selection systems and methodologies employed by various organizations. It discusses traditional approaches such as request for proposal (RFP), request for quotation (RFQ), and request for information (RFI) etc. Additionally, it explores more advanced techniques, including MCDM methods, data-driven approaches (relevant to the period of the research study), and optimization models.

Weber et al. [25] presented net price as the main evaluation criteria for any decision making process concerning supplier selection. The research work emphasizes that selecting vendors based on appropriate criteria is crucial to meeting customer demands and maintaining a competitive advantage. Furthermore, the research study discusses various methods and techniques used for vendor selection. These methods range from simple scoring models to more advanced MCDM approaches, such as Analytic Hierarchy Process (AHP) or Data Envelopment Analysis (DEA) etc. Each method has its own strengths and limitations, and the choice of method depends on the specific needs and requirements of the organization. The research work also highlights the importance of aligning the vendor selection criteria with the organization's strategic goals and objectives. It emphasizes the need for a structured and systematic approach to vendor selection that considers both quantitative and qualitative factors. Additionally, the authors have pointed out the usefulness of establishing metrics and indicators to assess vendors' performance regularly. This helps in identifying areas for improvement, addressing any communication issues, and ensuring that vendors consistently meet the organization's requirements.

Hong and Hayya [26] performed research supported by real-time data and determined that sourcing from multiple suppliers can reduce the total purchasing and inventory holding cost in a manufacturing setup based on just-in-time inventory system. The authors have discussed the advantages and disadvantages of both approaches. Single sourcing offers benefits such as simplified coordination, better communication, and potential cost savings through volume discounts. However, it carries the risk of disruptions if the sole supplier encounters issues. On the other hand, multiple sourcing provides diversification, flexibility, and reduced vulnerability to supplier problems. However, it may introduce complexity in coordination, communication, and logistics, potentially increasing costs. Additionally, the research work explores different scenarios and conditions under which one sourcing strategy might be more appropriate than the other. It suggests that in situations with high demand uncertainty, product complexity, or supply disruptions, multiple sourcing may be preferable to mitigate risks. Conversely, in stable demand conditions, with low product complexity, and strong supplier capabilities, single sourcing may offer cost and coordination advantages.

Wilson [27] analyzed the correlation among supplier selection criteria and concluded that cost, quality, timely delivery, and vendor service are the key characteristics for single supplier evaluation and selection. The research work highlights that supplier selection is a crucial decision that can significantly affect supply chain performance. The author has observed that the relative importance of supplier selection criteria can vary across industries, organizations, and specific contexts. The research study emphasizes the need for organizations to align their selection criteria with their strategic goals and requirements, as well as the characteristics of the products or services they procure. Furthermore, the author has highlighted the evolving nature of supplier selection criteria and notes that factors such as sustainability, innovation capability, and risk mitigation have become more important in recent years, reflecting the changing business landscape and emerging trends in supply chain management.

A survey by Swift [28] reported that price, availability, design, vendor's repute, and reliability are the key factors for evaluation of single or multiple suppliers. The author discusses the importance of conducting thorough assessments of potential suppliers to ensure their ability to meet these criteria. The research study examines the role of additional criteria, such as supplier flexibility, innovation capability, and social responsibility, in supplier selection. It emphasizes the growing importance of these criteria in today's business environment, where organizations seek suppliers who can adapt to changing demands, drive innovation, and demonstrate ethical and sustainable practices. The author emphasizes the need for a comprehensive and structured supplier selection process that considers both quantitative and qualitative factors. Furthermore, the importance of leveraging supplier performance data, conducting site visits, and engaging in effective communication and negotiation with potential suppliers has been highlighted.

It has been reported by Vonderembse and Tracey [29] that in manufacturing industry, quality, availability, reliability, and performance are the key evaluation criteria for supplier selection. The research work recognizes the critical role of suppliers in achieving manufacturing excellence and emphasizes the need for effective supplier selection processes. The authors have highlighted the importance of selecting suppliers based on appropriate criteria as it can positively impact manufacturing performance by ensuring reliable and high quality inputs, reducing lead times, and enhancing overall supply chain efficiency. Additionally, the research study explores the concept of supplier involvement, which refers to the extent to which suppliers are engaged in collaborative activities with manufacturers. It investigates the impact of supplier involvement on manufacturing performance indicators, such as product quality, delivery performance, cost efficiency, and innovation capability. The outcomes of the research study suggest that supplier involvement positively influences manufacturing performance. Close collaboration and communication with suppliers leads to improved product quality, reduced lead times, enhanced cost efficiency, and increased innovation. The research work highlights the significance of establishing strong and enduring partnerships with suppliers to drive manufacturing excellence and the need for continuous monitoring and evaluation of suppliers' performance to ensure ongoing improvement and alignment with organizational goals.

2.1.2 The Transition Era (2001-2010)

Ghodsypour and O'Brien [30] used purchasing cost and quality as assessment criteria to highlight the significance of single and multiple sourcing. The research work recognizes the importance of considering the total cost of logistics, which includes various components such as transportation costs, inventory costs, and order fulfillment costs, in the supplier selection processes. It notes that selecting the right suppliers while considering these cost factors is crucial for achieving supply chain efficiency and cost effectiveness. The authors have focused on scenarios where organizations have multiple sourcing options, multiple criteria to evaluate suppliers, and capacity constraints that limit the number of suppliers that can be selected. They present a comprehensive approach to address these complexities in supplier selection decisions. The research study discusses the formulation of the supplier selection problem as a mixed-integer linear programming (MILP) model that considers multiple objectives, including minimizing the total cost of logistics while satisfying capacity constraints and meeting predefined evaluation criteria. It presents mathematical formulations and optimization approaches that can be used to solve the supplier selection problem by applying different heuristic algorithms, such as Genetic Algorithm (GA), simulated annealing, and ant colony optimization to find near optimal solutions in complex scenarios.

A comprehensive review on multiple sourcing presented by Minner [31] highlighted that the practice of selecting more than one supplier can potentially enhance the bargaining power of the customer. Multiple suppliers can help the customer to successfully mitigate risks or disruption scenarios and offer competitive advantages between potential suppliers. The author has discussed different approaches, including deterministic and stochastic models, mathematical programming techniques, simulation methods, and optimization algorithms.

The research work highlights the importance of considering various factors in multiple supplier inventory models, such as supplier performance, pricing structures, transportation costs, and demand variability. It emphasizes the need to balance conflicting objectives, such as minimizing inventory holding costs while maintaining high service levels. The research study examines the impact of uncertainties and disruptions on multiple supplier inventory management. It further explores approaches for mitigating risks and enhancing supply chain resilience, such as safety stock policies, demand forecasting techniques, and contingency planning.

Ho et al. [32] analyzed the existing literature on supplier selection and determined that product price, quality, and delivery are the most important selection criteria. The research work focuses on the importance of supplier evaluation and selection in supply chain management and the need for robust decision making frameworks that consider multiple criteria. The authors have systematically analyzed a range of MCDM methods employed in supplier selection process including AHP, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), DEA, Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), and others. Each method is described in terms of its underlying principles, advantages, and limitations. The research study also highlights the need for a comprehensive evaluation framework that incorporates both quantitative and qualitative factors and accounts for the specific requirements and objectives of the organization.

2.1.3 Emergence of TBL Paradigm (2011 Onwards)

Chang et al. [33] carried out a study of literature to point out that cost, flexibility, quality, delivery reliability, capacity of related facilities, technology capability, lead time, reduction on demand change, environmental control, and service level are the top ten criteria taken into consideration during supplier selection process. The research study focuses on addressing the challenges of determining the relative importance of criteria during supplier selection process and highlights their significance in ensuring effective and efficient supply chain operations. However, assigning appropriate weights or importance to these criteria can be subjective and challenging due to uncertainties and vagueness in decision making. To overcome these challenges, the research work introduces the fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) method as a comprehensive and systematic approach. The fuzzy DEMATEL method applied in the research work combines the advantages of fuzzy logic and the DEMATEL technique to address the uncertainty and imprecision associated with criteria evaluation. The research work further outlines the step by step process of applying the fuzzy DEMATEL method for developing supplier selection criteria.

It involves the identification of criteria, construction of a fuzzy decision matrix, determination of the fuzzy correlation matrix, calculation of the fuzzy influence matrix, and the derivation of the final weightages for the criteria. The fuzzy DEMATEL method enables DMs to consider both the direct and indirect relationships among criteria, capturing the interdependency and interaction between them. The fuzzy logic component allows for the representation of linguistic variables and subjective judgments in the decision making process.

Four supplier evaluation and selection criteria i.e. cost, quality, service, and capacity have been identified by Kazemi et al. [34] while developing a mathematical programming model for supplier selection that incorporates uncertainty. The research work acknowledges that the SS-OA process involves complex decision making, as organizations need to consider various objectives such as cost minimization, quality maximization, delivery time optimization, and supplier capacity constraints.

Additionally, DMs often face uncertainty and imprecision in defining these objectives due to subjective judgments or incomplete information. The authors have addressed these challenges by incorporating fuzzy objectives in the mathematical model and propose a multi-objective mathematical programming approach that allows DMs to consider multiple conflicting objectives simultaneously.

Fuzzy objectives have been incorporated using FST, which helps DMs to represent and handle uncertain or imprecise objectives, as noted earlier. The model considers the trade offs between different objectives and provides a Pareto optimal solution set. DMs can analyze this solution set and make informed decisions based on their preferences or priorities.

It can be seen from the above discussion that in recent years different evaluation and selection criteria have been identified and used by various authors in published literature for SS-OA.

2.2 Sustainable Supplier Selection

The principles and practices of TBL sustainability have been integrated with supply chain management for past many years. Several research studies have been conducted to understand and highlight the utility and significance of integrating sustainability criteria with supply chain management [35].

An evaluation of the state of the art in sustainable supplier selection has been presented by Gimenez et al. [36] (assessment of managerial practices employed for sustainable supplier selection), Genovese et al. [37] (development of methodologies), and Igarashi et al. [38] (evolution of criteria and techniques).

2.2.1 Applications of Single MCDM Techniques

A framework for green supplier selection has been presented by Lee et al. [39] in which an MCDM technique has been employed for evaluating suppliers based on quality, life cycle cost, technical capability, greenhouse gas emissions, environmental monitoring, green competency, and recycling as major assessment criteria.

The research work addresses the increasing importance of environmental sustainability and the need for organizations in the high tech sector to identify suppliers that align with their green objectives. The research study introduces a green supplier selection model specifically tailored to the high tech industry. Furthermore, the authors emphasize the importance of collecting and evaluating data on supplier environmental performance through audits, certifications, and supplier self-assessment questionnaires.

A ranking model for sustainable supplier selection has been proposed by Amindoust et al. [40] based on cost, quality, technology capability, pollution, resource consumption, and information disclosure as the main sustainability attributes. The research work utilizes a Fuzzy Inference System (FIS) to develop a mathematical framework that can handle imprecise or uncertain data. The FIS aggregates the information from various criteria and calculates a comprehensive sustainability score for each supplier. This score represents the supplier's overall sustainability performance. By considering the linguistic variables and membership functions associated with each criterion, the model captures the subjective nature of sustainability assessments and provides a more accurate representation of supplier rankings. The proposed model provides a systematic and objective approach that can assist organizations in making informed decisions based on their specific sustainability goals and requirements.

A two phase hybrid model for green supplier selection has been proposed by Govindan and Sivakumar [41]. This model evaluates the potential suppliers using criteria such as cost, quality, timely delivery, recycling capability, and greenhouse gas emissions control. The research study addresses the challenge of integrating sustainability considerations into SS-OA decisions in an industry specific context. It proposes an integrated approach that combines heterogeneous Multi-criteria Group Decision Making (MCGDM) and multi-objective linear programming (MOLP) techniques. The MCGDM takes into account the diverse criteria and weights assigned to them by the DMs. The MOLP approach optimizes the allocation of orders among the selected suppliers while considering multiple conflicting objectives, such as minimizing costs, carbon emissions, and waste generation etc.

Neumuller et al. [42] have developed a mathematical model to create a collection of optimal strategic suppliers based on performance objectives and sustainability targets using a combination of Analytic Network Process (ANP) and Goal Programming (GP). The proposed model comprises of three main elements i.e. supplier assessment, supplier classification, and portfolio optimization. In the supplier assessment phase, the potential suppliers are evaluated based on their sustainability performance indicators such as environmental impact, social responsibility, and economic viability etc. This assessment helps identify suppliers that are aligned with sustainable practices and have a positive impact on the company's sustainability objectives. The next step is supplier classification that involves categorizing suppliers based on their sustainability performance scores. This classification enables companies to differentiate between suppliers and prioritize those that exhibit stronger sustainability practices. The last stage is portfolio optimization, which involves selecting suppliers for the strategic portfolio based on their sustainability performance.

Mohammed et al. [43] have presented a methodology for evaluating sustainable livestock suppliers on the basis of criteria such as price, technology, delivery rate, environmental and refuse management systems, pollution control, safety practices, and human resource development. The research work emphasizes the importance of incorporating uncertainty and risks into the decision making process.

It discusses the use of scenario analysis, sensitivity analysis, and risk assessment techniques to evaluate the robustness and resilience of the proposed methodology. By adopting the integrated methodology, organizations can make informed decisions that balance economic efficiency with sustainability considerations. The methodology provides DMs with a structured and comprehensive approach to address the two stage problem of SS-OA. It supports organizations in building a sustainable supply chain by selecting suppliers that align with sustainability goals and optimizing order allocation to minimize costs and environmental impact.

Lo et al. [44] have used a combination of ten sustainability criteria for supplier performance evaluation. The authors recognize the increasing importance of sustainability in supply chain management and propose an integrated methodology to effectively handle green SS-OA problems. The integrated methodology combines mathematical programming, MCDM methods, and optimization techniques to optimize SS-OA while considering environmental factors. The methodology takes into account criteria such as green performance, carbon emissions, waste management, and social responsibility when evaluating and selecting suppliers.

Furthermore, the methodology optimizes the allocation of orders among selected suppliers based on multiple objectives, including cost minimization, environmental impact reduction, and customer satisfaction. It considers trade offs and constraints to find the most optimal allocation that balances economic and environmental goals. The research work highlights the importance of data collection and analysis to support the model's implementation. The proposed integrated methodology has been demonstrated by implementing an application case study based on data collected from the electronics goods manufacturing industry.

Gören [45] has used thirteen different sub-criteria for assessing suppliers with regards to TBL aspects of sustainability. The sub-criteria have been analyzed through MCDM techniques for determining DM preferences. The framework proposed in this research work incorporates a mathematical model that optimizes SS-OA while accounting for the potential occurrence of lost sales. Lost sales refer to the situations where customer demand cannot be fulfilled due to supply shortages or other constraints. The research work highlights the importance of incorporating sustainability criteria into the decision framework through which companies can make more informed and responsible choices regarding their suppliers and order allocation strategies.

An MCDM technique coupled with fuzzy approach has been used by Memari et al. [46] to evaluate suppliers based on sustainability attributes like cost, quality, service, pollution reduction, green competency, and employment practices. This research work has been implemented through a case study based on automobile/automotive discrete parts manufacturing industry. The proposed framework addresses the complexities and uncertainties associated with sustainable supplier selection by incorporating intuitionistic fuzzy sets and TOPSIS.

The framework starts by identifying relevant sustainability criteria followed by application of intuitionistic fuzzy sets to handle the imprecision and uncertainty in assessing supplier performance against chosen criteria. TOPSIS is then utilized to rank potential suppliers based on their sustainability performance. The proposed methodology provides a structured approach to handle the uncertainty and complexities of sustainable supplier selection and supports organizations in making informed decisions that align with their sustainability goals. Khoshfetrat et al. [47] have used criteria such as cost, technology, environmental management system, green design practices, respect for rules and regulations, shareholders' rights, and human resource development for supplier evaluation and order allocation. The research work addresses the need for integrating sustainability considerations into SS-OA processes and proposes a fuzzy logic based methodology to handle the inherent uncertainty and vagueness in sustainable decision making. The authors have emphasized the significance of selecting suppliers that align with sustainability goals and allocating orders in a way that promotes sustainability throughout the supply chain network. The research study proposes a FIS that utilizes linguistic variables and fuzzy based rules to assess the sustainability performance of suppliers. The FIS aggregates different sustainability criteria and calculates a composite sustainability score for each supplier. This score helps DMs rank suppliers and make informed choices based on sustainability considerations. By adopting the fuzzy approach, DMs can effectively handle the complexities of sustainable SS-OA. The approach allows for the integration of multiple sustainability criteria, subjective judgments, and uncertainty, enabling organizations to make more sustainable and informed decisions in their supply chain operations.

Tirkolaee et al. [48] have used multiple MCDM techniques to evaluate suppliers engaged with an electronics goods supply chain using sustainability criteria such as cost, automation, product shelf life, environmental pollution, customer status, trust and communication, and human rights. The research work recognizes the challenge of dealing with imprecise and uncertain data and the need for a comprehensive decision making approach. For this purpose, the authors have proposed a hybrid method that combines fuzzy decision making and multi-objective programming (MOP). The fuzzy decision making process allows DMs to assess and quantify the qualitative and subjective aspects of supplier performance concerning sustainability and reliability criteria. This enables the representation and handling of uncertainty in the decision making process.

The MOP aspect of the hybrid method formulates an optimization model that balances the trade offs between conflicting objectives, such as minimizing environmental impact and maximizing reliability. The model helps identify the optimal set of suppliers that meet the sustainability and reliability requirements of the two echelon supply chain considered in this research work. Furthermore, the research study discusses the integration of the fuzzy decision making and MOP stages through an iterative process. This enables the DMs to adjust the decision criteria and weights, evaluate different supplier selection scenarios, and explore trade offs to achieve the desired sustainable and reliable supply chain design.

A dynamic decision support framework for sustainable supplier selection in the petro-chemical industry has been proposed by Alavi et al. [49]. This research work has employed multiple TBL sustainability criteria i.e. cost, quality, flexibility, waste and environmental management systems, occupational health and safety management, and child and forced labor issues for supplier assessment. The proposed framework employs mathematical models, data analytics, and visualization techniques to assess the sustainability performance of suppliers and support decision making processes. It provides a structured means to evaluate supplier options, ranking them based on sustainability criteria, and identifying the most suitable suppliers for an organization's specific needs and objectives.

It can be deduced from the above description that over the years, a variety of MCDM techniques and mathematical modeling approaches have been employed for sustainable supplier evaluation and selection i.e. AHP, ANP, TOPSIS, DEMATEL, Quality Function Deployment (QFD), DEA, VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Delphi method, Additive Ratio Assessment (ARAS) method, Adaptive Neuro (AN) FIS, Tomada de Decisao Interativa Multicriterio (TODIM), and Ordinal Priority Approach (OPA) etc. A classification of modeling approaches related to sustainable supplier selection, monitoring, and development has been presented by Zimmer et al. [50] and reproduced as Fig. 2.1.

2.2.2 Applications of Combined MCDM Techniques

In extant literature, a combination of two or more MCDM techniques has also been employed for criteria weighting and for evaluating the priority or ranking of sustainable suppliers. For instance, Zhou and Xu [51] have proposed an integrated MCDM model based on DEMATEL, ANP, and VIKOR for sustainable supplier selection in the retail industry. The research work focuses on integrating multiple sources of information and criteria to facilitate an effective decision making process. The authors have combined different sources of information, including expert opinions, customer preferences, and objective data, to evaluate and rank potential suppliers. The research study proposes the application of various techniques, such as AHP and Weighted Sum Model (WSM), to aggregate and analyze the information from different sources. These techniques facilitate the integration of subjective and objective data, enabling a more comprehensive evaluation of suppliers. Furthermore, the authors suggest the use of fuzzy sets and grey systems theory to handle vague and incomplete information, allowing DMs to make more informed and robust decisions. Zhang et al. [52] have proposed a framework for combining rough DEMATEL and fuzzy VIKOR for calculating weights of sustainability criteria and identifying the most suitable supplier. The rough DEMATEL method allows for the identification and assessment of the cause and effect relationships among evaluation criteria. It helps to understand the interdependencies and influences among criteria, providing a more accurate evaluation. The fuzzy VIKOR method, on the other hand, is a MCDM approach that considers both the benefits and costs associated with each alternative. It helps in ranking and selecting the most suitable sustainable suppliers based on their performance across multiple criteria. The authors have implemented the proposed approach through a numerical case study.

Hoseini et al. [53] have employed fuzzy Best Worst Method (BWM) for determining the weights of sustainability criteria followed by weighted FIS for the ranking of suppliers in the construction industry. The research work highlights the importance of sustainable supplier selection in this specific industry sector where factors such as economic viability, environmental impact, and social responsibility play crucial roles. The proposed methodology integrates fuzzy logic and MCDM techniques to evaluate and rank potential suppliers based on their sustainability performance. The research study utilizes a fuzzy based approach to handle the ambiguity and uncertainty associated with subjective judgments and linguistic expressions of DMs. The hybrid fuzzy based approach enables DMs in the construction industry to consider quantitative and qualitative factors simultaneously, facilitating a more holistic evaluation of supplier sustainability. By integrating fuzzy logic and MCDM techniques, the methodology provides a robust decision support tool for sustainable supplier selection. The authors have emphasized the practical applicability of the proposed approach and provided a case study to demonstrate its implementation. The case study illustrates how the methodology can effectively assess and select suppliers based on their sustainability performance, taking into account the specific requirements and objectives of construction projects.

A brief overview and comparison of relevant literature for sub-criteria and solving techniques applied for supplier selection has been included in Table 2.1.

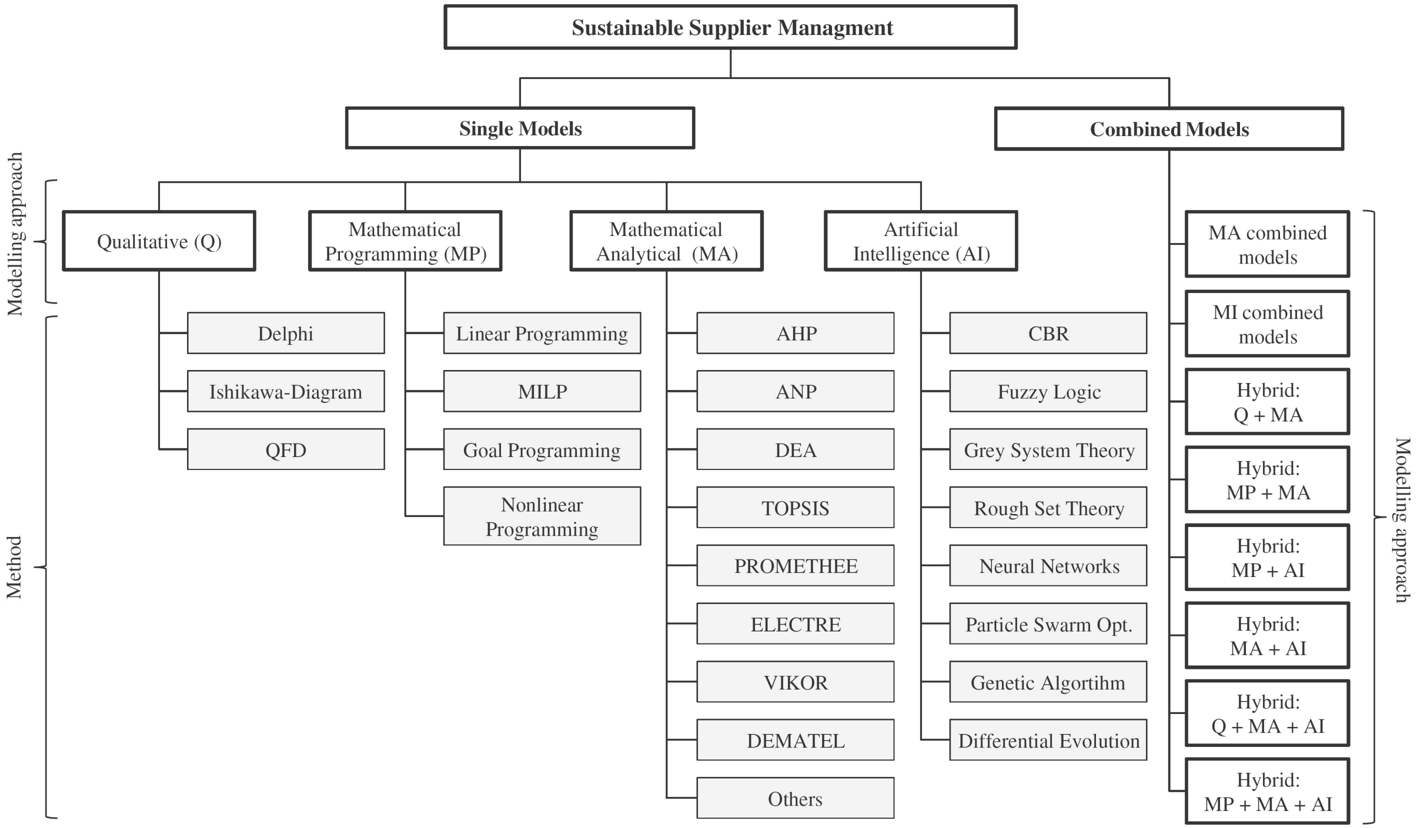


FIGURE 2.1: A classification of modeling approaches for sustainable supplier selection (from [50], with permission)

Boz et al. [54] have used a combination of fuzzy BWM and fuzzy ARAS method for sustainable supplier selection in the health care sector with a focus on optimizing logistics performance of the supply chain during COVID-19. The research work recognizes the increasing importance of sustainability in health care supply chains and the transformative impact of Logistics 4.0 technologies on supply chain operations.

The authors have proposed a novel MCDM model that incorporates multiple criteria, such as cost, quality, reliability, environmental impact, and social responsibility, into the supplier selection process. The research study highlights the significance of Logistics 4.0 technologies, such as Internet of Things (IoT), big data analytics, and artificial intelligence, in improving supply chain visibility, traceability, and overall performance in the health care sector. The proposed MC- DM approach takes into account the potential impact of these technological advancements while addressing sustainable SS-OA problem.

Out of all the techniques described above, AHP and TOPSIS or any variations of these two are the most frequently used MCDM techniques for sustainable supplier selection problem [7, 55]. A few instances from literature are presented here for illustrating the wide spectrum of application of these techniques.

Chai et al. [56] have provided an overview of the various decision making approaches and methodologies used in supplier selection and highlighted their strengths, limitations, and trends. The research work has adopted a systematic review methodology, analyzing a wide range of scholarly articles, conference papers, and other relevant sources. It identifies and categorizes decision making techniques employed in supplier selection, such as MCDM methods, mathematical programming models, fuzzy logic, DEA, and expert systems etc.

The authors have discussed the key features and characteristics of each decision making technique, highlighting their suitability for different supplier selection scenarios. They have examined the advantages and limitations of these techniques, considering factors such as complexity, data availability, DM preferences, and the treatment of uncertainty. Furthermore, the research study examines emerging trends and latest developments in the field of supplier selection decision making.

Table 2.1: Relevant literature for sub-criteria and solving techniques applied for supplier selection

Research Study	**Sub-criteria**	**MCDM Technique(s)**
Shabanpour et al. [57]	Cost, Quality, Financial ability, Eco-design, Energy consumption, Work safety and labor health	GP, DEA, Robust Charnes, Cooper, Rhodes (CCR) Model
Faisal et al. [58]	Quality, Price, On time delivery, Flexibility, Waste reduction and recycling, Environmental purchasing, Reverse logistics, Community initiatives, Ethical behavior, Health and safety, Workplace diversity	ANP
Ahmadian et al. [59]	Cost, Time, Quality, Embodied carbon, Embodied energy, Acoustic performance, Safety grade	Building Information Modeling (BIM), TOPSIS
Govindan et al. [60]	Cost, Delivery time, Quality certification, Lead time, Flexibility, Eco-design, Environment related certification, Staff training, Government regulations and legal compliance	Factor Analysis, AHP, k-means Clustering
Cheraghalipour and Farsad [61]	Cost, Quality, Delivery, Environmental commitment and management, Product performance, Greenhouse emissions, Occupational and worker health and safety, Social commitment and management, Wages and working hours	BWM

Memari et al. [46]	Cost, Quality, Service, Environmental efficiency, Pollution reduction, Green competency, Safety and health, Employment practices	Fuzzy TOPSIS
Tavassoli and Saen [62]	Cost, Quality, Delivery, Supplier experience, Energy consumption, Work safety and labor health	Stochastic DEA, Discriminant Analysis (DA)
Tirkolaee et al. [48]	Cost, Flexibility, Automation, Product shelf life, Integration and partnership, Market imbalances recognition, Quality improvement, Customer status, Trust and communication, Development of culture and technology	Fuzzy ANP, Fuzzy DEMATEL, Fuzzy TOPSIS
Alavi et al. [49]	Cost, Quality, Delivery, Reputation, Flexibility, Financial capability, Waste management, Environmental management system, Respect for environmental regulations and standards, Utilizing clean and green technology, Attention to energy consumption and air pollution, Human rights, Occupational health and safety management system, Information disclosure, Social commitment, Child and forced labor problem	Fuzzy BWM, FIS
Tayyab and Sarkar [63]	Cost, Quality, Time, Energy consumption, Carbon emissions	Interactive Weighted Fuzzy GP

It discusses the integration of sustainability criteria, the use of hybrid approaches that combine multiple techniques, the incorporation of machine learning and artificial intelligence, and the application of decision support systems. The review also identifies gaps and areas for further research, emphasizing the need for more comprehensive and integrated decision making models that consider sustainability, resilience, and dynamic factors in supplier selection.

Awasthi et al. [64] have developed a multi-phase framework based on fuzzy TOPSIS for evaluating suppliers using environmental criteria. The proposed framework considers various environmental factors, such as carbon emissions, waste management, energy efficiency, and water usage, among others, while taking into account the subjective nature of sustainability assessment as well. The framework has been demonstrated by implementing an application case study problem.

Büyüközkan and Cifci [65] have used a composite framework employing DEMATEL, ANP, and TOPSIS to select green suppliers. The techniques considered in this research work allow for a comprehensive evaluation of green supplier attributes. Furthermore, all MCDM techniques have been fuzzified to incorporate real-world uncertainty. The fuzzy DEMATEL method is used to identify and analyze the interrelationships among various green supplier criteria, such as environmental impact, energy efficiency, waste management, and social responsibility. The fuzzy ANP approach helps determine the relative importance and weights of these criteria. Finally, the fuzzy TOPSIS technique ranks the green suppliers based on their performance against the identified criteria. By integrating these three methods, the composite framework offers a more accurate and comprehensive assessment of green suppliers.

Kannan et al. [6] have employed fuzzy TOPSIS supported by ad hoc weights to evaluate green suppliers. In this research work, MOP has been used for order allocation. The green criteria considered for supplier selection may include factors such as environmental performance, carbon emissions, waste management, and social responsibility. The authors have taken into account both quantitative and qualitative factors, and weights are assigned to different criteria based on their relative importance. Multiple conflicting objectives, such as minimizing costs and carbon emissions, while maximizing customer satisfaction, are considered and optimized simultaneously for determining optimal order allocation quantities.

Freeman and Chen [66] have used TOPSIS combined with entropy method and AHP for evaluating and ranking sustainable suppliers. The research work highlights that selecting green suppliers is crucial for organizations aiming to incorporate sustainability practices into their supply chains. The authors have introduced the AHP-Entropy-TOPSIS framework as a comprehensive approach to evaluate and rank potential green suppliers. The AHP method is used to determine the relative weights of criteria, considering both environmental and non-environmental factors. The entropy method is applied to calculate the objective weights of criteria, reducing subjectivity and bias. Finally, TOPSIS is utilized to rank the suppliers based on their performance against the identified criteria. The proposed framework allows DMs to consider a wide range of criteria, including environmental impact, energy efficiency, waste management, cost, quality, and delivery performance etc. By incorporating objective weights through entropy and considering both quantitative and qualitative factors, organizations can make more informed decisions that align with their green supply chain objectives.

An AHP and VIKOR method based sustainable supplier evaluation and ranking approach has been proposed by Luthra et al. [67]. The authors have introduced a framework that combines TBL dimensions of sustainability to guide the supplier selection and evaluation process. This integrated framework consists of several stages. It begins with the identification of sustainability criteria relevant to the organization and the supply chain context. These criteria may include factors such as greenhouse gas emissions, labor practices, waste management, and product life cycle considerations. Next, the framework incorporates various assessment tools and methods to evaluate suppliers against the identified sustainability criteria. These tools may include questionnaires, audits, certifications, and performance indicators. The evaluation process provides a holistic overview of suppliers' sustainability performance and enables organizations to make informed decisions. The proposed framework emphasizes the importance of collaboration and engagement with suppliers throughout the process. Effective communication, sharing of sustainability goals, and establishing mutual expectations are crucial for developing sustainable partnerships with suppliers.

Mohammed et al. [43] have applied fuzzy AHP and fuzzy TOPSIS for supplier selection in a livestock supply chain network based on TBL sustainability criteria. The authors have adopted a three phase methodology. In the first phase, fuzzy AHP has been used for calculating local weights of the chosen sub-criteria. In the second phase, fuzzy TOPSIS has been applied for ranking suppliers using global weights of the conventional, green, and social criteria. In the last phase of the proposed methodology, a multi-objective mathematical model has been developed for calculating optimal order allocation quantities. TOPSIS has been once again applied for assisting DMs in identifying the best solution from the set of Pareto optimal solutions generated by the optimization methods employed during the order allocation phase.

Yadavalli et al. [68] have used fuzzy TOPSIS for sustainable supplier assessment and selection aimed at home appliances manufacturing industry. The research paper emphasizes the importance of considering customers' perspectives and sustainability factors in supplier selection processes. The authors acknowledge the increasing demand for sustainable products and the growing influence of customers' expectations on supply chain decisions. They have presented an integrated optimization model that combines customer expectations and sustainability criteria. The model aims to identify suppliers that can meet customer requirements while demonstrating sustainable practices. It incorporates factors such as price, product quality, delivery performance, and environmental and social responsibility. The optimization model considers both quantitative and qualitative data, allowing DMs to assign weights to different criteria based on customer preferences.

Mohammed et al. [69] have proposed a multi-objective optimization model that employs fuzzy AHP and fuzzy TOPSIS for evaluation of suppliers based on sustainability criteria. The research work emphasizes the importance of considering trade offs between conflicting objectives and the need to involve DMs' preferences and priorities. The proposed hybrid approach enables DMs to explore different alternatives and make informed decisions that align with their sustainability goals while achieving economic efficiency. The research study offers a structured framework for assessing suppliers using sustainability criteria and optimizing order allocation to balance multiple objectives. The outcomes of the research study can support organizations in building a sustainable supply chain and making decisions that contribute to environmental responsibility and social well being.

A combined Delphi method, fuzzy TOPSIS, and MOP approach has been presented by Rabieh et al. [70] for evaluating suppliers using TBL sustainability attributes. The integrated approach starts with the Delphi method, which involves gathering expert opinions through a structured questionnaire and iterative rounds of consensus building. The Delphi method helps identify and prioritize relevant sustainability criteria, considering the opinions and expertise of multiple stakeholders. Next, the fuzzy TOPSIS is employed to evaluate and rank potential suppliers based on their performance against the identified sustainability criteria. Fuzzy logic allows for the consideration of imprecision and uncertainty in the evaluation process. Fuzzy TOPSIS calculates the proximity of each supplier's performance to the ideal solution and the distance from the negative ideal solution, facilitating the identification of suppliers that offer the best trade offs between sustainability objectives. Lastly, a MOP model is applied to optimize the allocation of orders among selected suppliers. The model considers various objectives such as cost minimization, carbon emissions reduction, and customer satisfaction. It aims to find the Pareto optimal solutions that balance these objectives and meet sustainability constraints. The approach promotes responsible sourcing, reduces environmental impact, and supports DMs in building a sustainable supply chain.

Okwu and Tartibu [71] have developed an integrated TOPSIS and ANFIS methodology for sustainable supplier selection to be used in consumer goods supply chain. The proposed methodology begins by identifying and defining sustainability criteria relevant to the retail industry. These criteria may include factors such as environmental impact, social responsibility, ethical sourcing, product quality, and delivery reliability. TOPSIS is then employed to evaluate and rank potential suppliers based on their performance against the identified sustainability criteria. Additionally, the authors have introduced the use of ANFIS, a hybrid computational intelligence technique that combines the advantages of fuzzy logic and neural networks. ANFIS is utilized to handle uncertainty and imprecise information in the decision making process, providing more accurate and robust evaluations of supplier sustainability.

In developing countries, solar photovoltaic (PV) systems dominate the renewable energy landscape. Liaqait et al. [72] have focused on sustainable SS-OA, considering the unique characteristics and sustainability requirements of the solar PV industry. The authors acknowledge the growing importance of sustainability in the renewable energy sector and the need for sustainable practices within the solar PV panels supply chain. They propose a decision framework that integrates sustainability considerations into SS-OA processes. The decision framework encompasses several stages. It begins with the identification and evaluation of potential suppliers based on their sustainability performance. Criteria such as economic viability, environmental impact, and social awareness are considered to assess the suppliers' sustainability credentials. Once suppliers are selected, the framework moves to the order allocation stage. It aims to allocate orders to suppliers in a way that optimizes sustainability performance while considering factors such as product price, product quality, and timely delivery. The allocation decisions are made by using a multi-objective optimization approach.

Liaqait et al. [73] have proposed a decision support framework that integrates multiple supplier selection criteria and order allocation objectives to facilitate sustainable decision making. The proposed framework employs multi-objective optimization techniques to balance conflicting objectives such as cost minimization, environmental impact reduction, and social responsibility. By considering multiple objectives simultaneously, DMs can explore trade offs and identify optimal solutions that align with their sustainability goals. Fuzzy logic has been incorporated in the proposed framework to handle uncertainty and vagueness in decision making. The framework provides DMs with a structured and systematic approach to make informed decisions, optimizing sustainability outcomes, and enhancing the overall sustainability performance of the supply chain. The proposed decision framework has been demonstrated by implementing a case study from the refrigeration and air-conditioning industry.

It is evident from the above description that AHP and TOPSIS are two of the most flexible and diversely used quantitative multi-attribute assessment and decision making techniques employed for sustainable supplier selection.

2.3 Sustainable Order Allocation

A detailed review and meta-analysis of recent research work related to sustainable order allocation has been presented by Ghadimi et al. [74] (buyer-supplier relationships) and Di Pasquale et al. [75] (criteria, models, and planning techniques).

2.3.1 The Traditional Approach

Order allocation is a complex multi-variable decision problem. Over the years different mathematical models have been developed and solved using various optimization techniques. For example, Aissaoui et al. [5] have presented a review that covers supplier selection and order lot sizing in detail. The supplier selection process aims to evaluate and select those suppliers that can best meet the requirements and objectives of the organization. Order lot sizing refers to determining the optimal quantity of products or materials to order from the selected suppliers. This decision is crucial as it affects costs, inventory levels, and overall supply chain performance. The review presents and compares different mathematical models and approaches that have been proposed to address order lot sizing challenges and optimize decision making. The research work further explores various factors that influence supplier selection and order allocation, including demand variability, lead time, transportation costs, and economies of scale. It also highlights the importance of considering uncertainties and risks in decision making processes. The authors have classified the available literature on order allocation on the basis of single or multiple sourcing approaches. Within multiple sourcing category, they have further subdivided the order allocation activity into single and multi-period models (Fig. 2.2). The authors have observed that during multi-period order allocation, it is rarely the case that time depending parameters like dynamic demand or time-varying price discounts etc. are taken into account despite the fact that

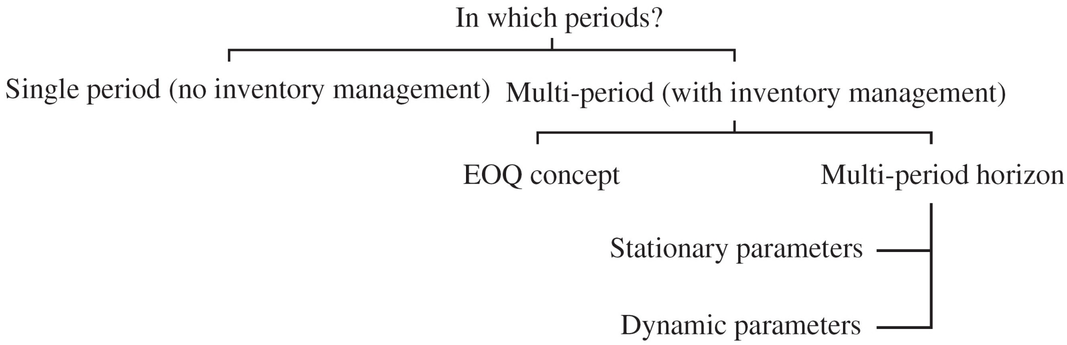


Figure 2.2: Classification of order allocation approaches based on single and multi-period models (from [5], with permission)

these parameters have a considerable effect on supplier efficiency and customer requirements.

Faez et al. [76] have proposed a scenario based MILP model for order allocation and solved it using LINGO optimization modeling software. The research work recognizes the complexities and uncertainties involved in decision making processes and proposes a hybrid model that combines fuzzy case based reasoning and mathematical programming. It emphasizes the importance of selecting the right vendors and allocating orders optimally to ensure efficient supply chain operations. It highlights the need to consider multiple criteria, such as cost, quality, delivery performance, and capacity, while addressing the inherent uncertainties and vagueness in decision making. The fuzzy case based reasoning approach allows for the handling of subjective and imprecise information, enabling DMs to draw upon past experiences and similar cases to make informed judgments. The mathematical programming component provides an optimization framework to allocate orders among selected vendors based on the defined criteria and constraints. The research study discusses the implementation process of the integrated model, including the collection and analysis of historical data, the construction of fuzzy case libraries, and the formulation of mathematical programming models. It demonstrates how the model can effectively evaluate and rank vendors, considering both quantitative and qualitative factors. The research work further highlights the benefits of the integrated approach, such as improved decision making accuracy, enhanced efficiency, and the ability to handle uncertainty and subjective assessments. The research concludes by presenting case studies to showcase the application and effectiveness of the integrated model in vendor selection and order allocation. It demonstrates how the model can be customized and adapted to different supply chain contexts, considering specific requirements and objectives.

2.3.2 Development of Hybrid Models

A fuzzy MILP model subject to variable price and product uncertainty conditions has been proposed by Nazari-Shirkouhi et al. [77]. The model has been solved using an exact algorithm for determining optimal order quantities. The research work recognizes the significance of selecting the right suppliers and allocating orders efficiently to ensure smooth operation of the supply chain. The proposed approach considers multiple objectives and incorporates FST to handle uncertainty and vague information in decision making. Fuzzy logic is employed to represent and handle the subjective judgments and imprecision associated with the supplier evaluation and selection criteria. In the order allocation stage, the calculation and assignment of order quantities to the selected suppliers is carried out by considering factors such as cost, demand, and supplier capacities. The approach enables DMs to generate Pareto optimal solutions that represent the best compromise among conflicting objectives.

A MILP model has been presented by Torabi et al. [78] taking into account uncertainty and disruption risks. The model has been optimized using Augmented ε-Constraint (AUGMECON) method and DEA. The authors have noted that supply chain networks face various risks, including operational risks such as demand variability and capacity constraints, as well as disruption risks such as natural disasters, geopolitical events, and supplier failures etc. They emphasize the need to consider these risks when selecting suppliers and allocating orders to ensure the continuity and resilience of the supply chain. The have further proposed a decision making framework that integrates SS-OA processes. The framework aims to identify resilient suppliers based on their capabilities to mitigate risks and to recover quickly from disruptions. It considers both quantitative and qualitative factors, such as supplier reliability, financial stability, geographical location, and risk management practices. The research work also discusses the allocation of orders among selected suppliers to minimize the impact of risks. It proposes a

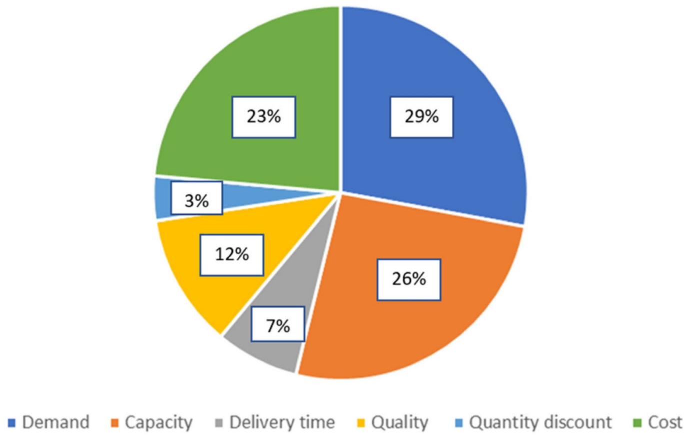


Figure 2.3: Sources of uncertainty (from [23], with permission)

mathematical model that optimizes order allocation based on supplier capabilities, costs, and risk mitigation strategies. The model aims to strike a balance between risk mitigation and operational efficiency, ensuring the resilience of the supply chain while maintaining cost effectiveness. Additionally, the research study highlights the importance of considering lead time and inventory management in the decision making process. It emphasizes the need for robust inventory policies and supply chain coordination to enhance responsiveness and to mitigate the effects of disruptions, whether natural or manmade.

Naqvi and Amin [23] have analyzed the extant literature related to SS-OA, published between the years 2015-20 and observed that among the uncertain optimization models proposed, the most popular sources of uncertainty considered are demand, capacity, and cost, respectively. Customer demand has been the leading factor in 29% of the research articles analyzed in this review, and it is usually incorporated as a constraint in optimization models developed for order allocation (Fig. 2.3).

Çebi and Otay [79] have developed a MILP model with multiple product uncertainty and quantity discounts and optimized it using augmented maximum-minimum and fuzzy GP algorithms to determine order allocation quantities. The research work recognizes the complexity of supplier evaluation and order allocation decisions, which involve multiple factors such as cost, supplier performance, quantity discounts, and lead time. The research presented by the authors aims to provide a comprehensive framework that considers these factors and incorporates fuzzy logic to handle uncertainties and subjective assessments. In the first stage of the proposed framework, the authors have developed a fuzzy evaluation model to assess and rank potential suppliers based on various criteria such as cost, quality, reliability, and environmental factors. Fuzzy logic allows DMs to express their subjective judgments and preferences in a more flexible manner. During the second stage, a fuzzy order allocation model has been implemented to determine the optimal order allocation quantity for each selected supplier. The model considers quantity discounts offered by suppliers, lead time constraints, and other relevant factors to minimize total cost while meeting the desired service level.

A weighted fuzzy MOLP model has been presented by Bodaghi et al. [80]. This model addresses the integrated supplier selection, order allocation, and customer order scheduling problem for a make-to-order manufacturing system. An algorithm has also been proposed in this research work to solve the model and the model has been implemented using a numerical problem. The model aims to optimize supplier selection decisions while considering various factors such as product price, quality, delivery rate, and supplier reliability. The integration of fuzzy logic allows for the handling of imprecise and uncertain data, enabling a more realistic and flexible assessment of suppliers. The weighting mechanism assigns importance to different criteria based on their relative significance, allowing DMs to customize the model based on their specific requirements and preferences. The research work emphasizes the benefits of the integrated model in achieving a balanced approach to SS-OA. By considering multiple objectives and uncertainties, organizations can make informed decisions that align with their supply chain goals and optimize overall performance.

Di Pasquale et al. [75] have carried out an extensive and in depth evaluation of the order allocation literature spanning the duration 1979-2018. The authors have focused on identifying and analyzing articles that have considered order allocation separately from supplier selection. The authors have noted that mathematical programming is the most preferred method for order allocation among the research papers analyzed owing to the multi-objective nature of the optimization problem. The review also highlights that multi-period and multi-product optimization problems form the major category of problems addressed in published literature. It has

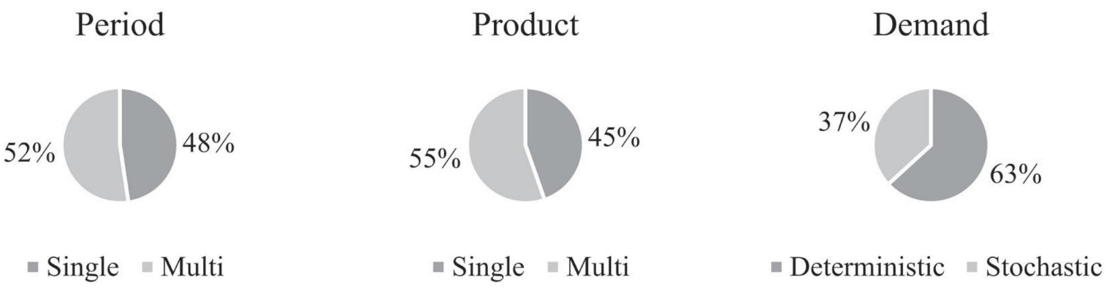


FIGURE 2.4: Distinguishing features of order allocation models (from [75], with permission)

also been observed that only 37% of the reviewed research articles have considered stochastic demand (Fig. 2.4). In this regard, many articles have inadvertently classified fuzzy demand as stochastic as well.

Sustainable order allocation is usually carried out using well defined and distinct objectives like cost, travel time, environmental impact, or any social criterion etc. Depending on the nature of the order allocation problem, single or multi-objective models may be formulated. A multi-objective mathematical programming model has been developed by Azadnia et al. [81] that minimizes total cost and environmental impact, and maximizes total social score and total economic qualitative score for optimal order allocation to the selected suppliers. The research work takes into account both supplier selection and order lot sizing considerations. The proposed model integrates sustainability criteria such as economic viability, environmental impact, and social responsibility, along with cost, quality, and delivery performance metrics. The decision making process involves evaluating and ranking potential suppliers based on their sustainability performance and assessing the optimal order lot sizing decisions to minimize costs while meeting stated sustainability objectives. In order to solve the multi-objective optimization problem, the authors propose using a suitable mathematical programming technique that can generate a set of Pareto optimal solutions. These solutions represent trade offs between different objectives and allow DMs to choose the most appropriate supplier and order lot sizing strategy based on their preferences. The research work emphasizes the practical applicability of the proposed approach by providing an application case study.

Govindan and Sivakumar [41] employed TOPSIS and a linear programming model to minimize cost, acceptable quality limit, late arrival, recycling waste, and greenhouse gas emissions. The research work addresses the challenge of integrating sustainability considerations into SS-OA decisions in an industry specific context by combining heterogeneous MCGDM and MOLP techniques. The MCGDM approach takes into account the diverse criteria and weights assigned to them by the DMs. Subsequently, the research integrates the results of the supplier evaluation into a MOLP model. The MOLP model optimizes the allocation of orders among the selected suppliers while considering multiple conflicting objectives, such as minimizing costs, carbon emissions, and waste generation. By combining these approaches, the research study aims to support DMs in making sustainable choices in SS-OA, taking into account both quantitative and qualitative criteria. The research article contributes to the field by presenting a novel framework specifically designed for the low-carbon paper industry, offering insights into the decision making processes in the context of sustainability in this particular industry sector.

A mixed-integer nonlinear programming (MINLP) model has been proposed by Hamdan and Cheaitou [82] as part of a framework that maximizes total value and minimizes total cost. The framework aims to support DMs in making informed choices that balance economic and environmental objectives. The research work incorporates an MCDM process that evaluates potential suppliers based on various green criteria, such as carbon footprint, energy efficiency, waste management, and pollution prevention. Different MCDM methods, such as AHP, TOPSIS, and WSM, are employed to rank and select suppliers based on their green performance. Furthermore, the research study incorporates multi-objective optimization to determine order allocation quantities for the selected suppliers. The optimization model aims to minimize total costs and environmental impact, taking into account factors such as transportation costs, order quantities, and carbon emissions. By combining MCDM and multi-objective optimization, the methodology enables DMs to evaluate suppliers based on their green criteria and allocate orders in a way that optimizes economic and environmental objectives simultaneously. A case study has also been presented that demonstrates how the methodology can effectively evaluate suppliers, allocate orders, and support decision making processes in a real-world context.

Gören [45] has applied fuzzy DEMATEL for calculating weights of sustainability criteria. These weights are used as inputs in Taguchi loss functions for ranking the potential suppliers. The rating values of suppliers are subsequently used for determining optimal order allocation quantity for each selected supplier through bi-objective optimization i.e. minimizing total cost while maximizing total sustainable purchasing. The author has demonstrated the practical applicability of the proposed integrated framework using data from the travertine/marble processing industry under deterministic customer demand conditions.

Moheb-Alizadeh and Handfield [83] have proposed a multi-objective MILP model that incorporates total cost, carbon emissions, and social responsibility as the three principal objective functions where cost and emissions are to be minimized while social responsibility is to be maximized. The proposed model aims to optimize SS-OA by finding a set of Pareto optimal solutions that represent the best trade offs between conflicting objectives. In order to solve the model, the authors have introduced a hybrid solution approach that combines mathematical programming and metaheuristic algorithms. This approach leverages the strengths of both methods to improve the efficiency and effectiveness of the solution process. The research work further emphasizes the significance of incorporating sustainability constraints and preferences into the model. DMs can specify sustainability related constraints, such as carbon emissions limits or waste reduction targets, and express their preferences for different sustainability objectives.

You et al. [84] have proposed an integrated methodology employing a MOLP model that minimizes total cost, defective item rate, and late delivery while at the same time maximizing the total value of sustainable purchasing. The authors have used Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA) method for determining the weights of the selection criteria and ranked the potential sustainable suppliers using extended Decision Field Theory (DFT). The research work recognizes the need to consider multiple criteria, such as cost, quality, environmental impact, social responsibility, and delivery reliability, to ensure the selection of suppliers aligned with sustainability goals. The proposed approach integrates MCDM techniques, such as AHP and TOPSIS, with MOLP to formulate an optimization model. The model aims to identify sustainable suppliers and allocate orders optimally based on multiple objectives, including sustainability performance, cost efficiency, and customer satisfaction. The MCDM techniques enable DMs to assess the relative importance of criteria and evaluate the performance of suppliers based on these criteria. The MOLP component considers the trade offs among conflicting objectives to determine the Pareto optimal solutions that provide the best compromise between different objectives.

A multi-objective integer linear programming (MOILP) model has been proposed by Beiki et al. [85]. The model intends to minimize total cost and carbon footprint while maximizing the total value of sustainable purchasing. The research work presents a comprehensive approach that combines sustainability criteria with cost and quality considerations in the SS-OA process. The authors have employed Language Entropy Weight Method (LEWM) for supplier assessment and selection, while the decision variables have been formulated and optimized through the aforementioned mathematical programming technique. The research work highlights the practical application of the unified approach by using an application case study from the automobile manufacturing industry. It demonstrates the implementation of the decision making process, the evaluation of different supplier options, and the optimal allocation of orders based on the integrated sustainability and operational objectives.

A variety of exact, heuristic, and metaheuristic problem solving algorithms have been used for evaluating and optimizing objective functions for sustainable order allocation. AUGMECON, WSM, Weighted Additive Model, GP, Dynamic Programming, GA, and DEA are some of the frequently used techniques in published literature as reported by Rashidi [86]. This meta-review further explores various methodologies, models, and criteria used in the literature to evaluate and select sustainable suppliers and to perform robust order allocation based on TBL sustainability considerations. It examines multiple studies and synthesizes their findings to identify common trends, challenges, and gaps in the field. The author has highlighted the need for a holistic approach that considers multiple dimensions of sustainability such as economic viability, environmental impact, and social responsibility in both supplier selection and order allocation parts of the SS-OA problem.

A brief overview and comparison of relevant literature for mathematical models, objectives, and solution approaches employed for order allocation has been included in Table 2.2.

2.4 Sustainable and Resilient Supplier Selection and Order Allocation

Different approaches have been adopted by researchers for evaluating supply chain network performance under the influence of natural or manmade disruptions. The response of the supply chain when subjected to such mishaps is almost always associated with the inherent resilience of the supply chain network and/or its components. Resilience can be considered a performance evaluation criteria alongside TBL sustainability in SS-OA problems and its sub-criteria can be identified in the same manner as economic, environmental, or social sub-criteria. This integration of TBL sustainability and resilience parameters leads to a single coherent supply chain management paradigm that can be represented by the 04 sides of a performance evaluation pyramid (Fig. 2.5). The 04 sides of the pyramid are the four points of view for the DMs, through which they can analyze the design and functioning of the supply chain network or any of its nodes or links in a holistic manner.

As the combination of TBL sustainability with SS-OA transformed it into sustainable supplier selection and order allocation or SSS-OA problem, the grouping of resilience with sustainability criteria will transform it into sustainable and resilient supplier selection and order allocation or SRSS-OA problem. A resilience based supplier selection approach has been presented by Rajesh and Ravi [87] using Grey Relational Analysis (GRA), AHP, and ANP. Supply chain velocity, supply chain visibility, supply chain vulnerability, and supply chain continuity management are some of the resilience sub-criteria included in this research work. The authors acknowledge the increasing importance of resilience in supply chain management, particularly in the face of uncertainties and disruptions, and highlight the need to select suppliers that can effectively contribute to the resilience of the supply chain.

TABLE 2.2: Relevant literature for mathematical models, objectives, and solution approaches for order allocation

Research Study	**Mathematical Model**	**Objectives**	**Solution Approach**
Babbar and Amin [88]	Stochastic MILP	Total cost, Defect rate, Carbon emissions, Supplier weights, On time delivery	Fuzzy QFD
Gören [45]	Bi-objective mixed-integer programming (MIP)	Total cost, Total value of purchasing	Weighted Comprehensive Criterion Method
Hadian et al. [89]	MOLP	Total cost, Defect rate, Late delivery, Total purchase value	AHP
Hu et al. [90]	Multi-objective MINLP	Total profit, Stakeholders satisfaction	GA
Aggarwal et al. [91]	Multi-objective optimization	Total cost, Total quality of purchased products, Total lead time	Chance Constrained Approach

Arabsheybani et al. [92]	Multi-objective non-linear programming (MONLP)	Total profit, Lost sale balance, Total discount risk	Fuzzy GP
Yadavalli et al. [68]	Bi-objective MILP	Total cost, Sustainable value purchase	Weighted GP
You et al. [84]	MOLP	Purchasing cost, Defective quantity, Delayed delivery quantity, Total sustainable value of purchasing	LP-metric Method
Beiki et al. [85]	MOILP	Total cost, Total carbon emission, Total purchase value	Max-min Operator Method
Nasr et al. [93]	Multi-objective MILP	Total cost, Environmental impact, Employment opportunity, Lost sales, Procurement value	Fuzzy BWM

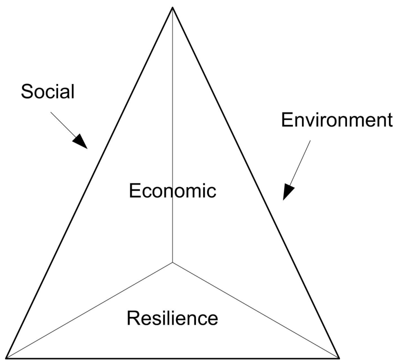


Figure 2.5: Integrated TBL sustainability + resilience performance evaluation pyramid

The proposed approach, GRA, is a decision making technique that can handle uncertainties and vagueness in supplier evaluation. GRA involves converting quantitative or qualitative data into grey numbers and calculating the grey relational coefficient to determine the relative closeness between alternatives. The research work explains that GRA approach allows DMs to evaluate suppliers based on multiple criteria, such as financial stability, flexibility, risk management capabilities, and responsiveness to disruptions. It provides a systematic and quantitative method to assess supplier performance in terms of resilience. By applying GRA, DMs can rank potential suppliers based on their grey relational grade, with higher grades indicating stronger resilience performance. This ranking helps organizations identify suppliers that can contribute to the resilience of their supply chain and mitigate risks associated with disruptions. The research study also highlights the importance of considering the specific context and requirements of the supply chain when applying GRA. The selection criteria and weightages should be customized to the unique needs and characteristics of the supply chain under consideration.

Hosseini et al. [12] have evaluated the resilient SS-OA problem using sub-criteria such as backup supplier, surplus and restorative capacity, and supplier segregation. They have used stochastic bi-objective MIP for both supplier selection and order allocation. The research work emphasizes the importance of supply chain resilience in mitigating risks and ensuring continuity of operations. The authors have incorporated disruption risks into the supplier selection process by considering factors such as supplier reliability, geographical location, financial stability, and contingency planning with the aim to identify suppliers that are resilient and capable of withstanding potential disruptions. Furthermore, the research study optimizes the allocation of orders among selected suppliers while minimizing total cost and potential disruption impact.

Mohammed et al. [94] have integrated resilience with economic and environment criteria for network design in livestock supply chain using MCDM techniques and fuzzy MOP. Social sub-criteria have not been considered in this research work. The research work aims to optimize the design of a supply chain network by considering multiple objectives such as cost minimization, carbon emissions reduction, transportation efficiency, and supplier reliability. Fuzzy logic has been used to handle uncertainties and subjective judgments associated with these objectives.

Yavari and Zaker [95] have developed a supply chain network by combining economic, environmental, and resilience criteria using MILP. The social dimension of sustainability has been excluded from this research work also and only one resilience sub-criteria has been considered i.e. power disruption. The research work acknowledges the challenges of managing perishable products in supply chains, including their vulnerability to disruptions and the importance of sustainable practices. It emphasizes the need for a resilient and environmentally friendly supply chain design that can effectively cope with disruptions while minimizing environmental impact. The authors have introduced a two layer network model that integrates the design of the supply chain and distribution of perishable products within the network. The model incorporates various factors, such as facility location, transportation routes, inventory management, and product recovery, to optimize the design of a potentially resilient and green closed loop supply chain. Additionally, the research study aims to identify optimal strategies for mitigating disruptions, such as contingency plans, alternative sourcing, or re-routing of transportation. It also emphasizes the importance of incorporating closed-loop practices into supply chain design while addressing issues like product recovery, recycling, and re-manufacturing, with the objective of minimizing waste and promoting sustainability. The closed-loop approach enables the reuse and recycling of materials, reducing the environmental footprint of the supply chain. The findings of the research work demonstrate the effectiveness of the proposed model in designing a resilient, green, and closed-loop supply chain for perishable products.

A supplier selection approach has been presented by Xiong et al. [96] based only on environmental and resilience criteria. In this research work Weighted Aggregated Sum Product Assessment (WASPAS), BWM, and TOPSIS have been used to evaluate suppliers using surplus inventory, factory segregation, and reorganization as resilience sub-criteria. The social aspect of TBL sustainability has been omitted from the supplier evaluation process in this research work as well. To address the complexities of supplier selection, the authors propose a multi-step approach. Firstly, the WASPAS method is employed for assigning weights to the criteria and sub-criteria, reflecting their relative importance in the decision making process. Secondly, the BWM method is used for determining the best and worst alternatives for each criterion, providing insights into the strengths and weaknesses of suppliers in relation to the selected criteria. Lastly, TOPSIS is applied to rank the suppliers based on their overall performance and determine the most suitable supplier for selection.

A state of the art review that deals with analyzing the development of SRSS-OA as an emerging research area has been presented by Negri et al. [97].

An overview and comparison of relevant literature for SRSS-OA has been included in Table 2.3. (In this table and in all subsequent tables in the following chapters, EC = Economic Criteria, E_nC = Environment Criteria, SC = Social Criteria, and RC = Resilience Criteria, when used.)

2.5 Supply Chain Disruptions and Service Level

A detailed assessment of research publications related to supply chain network disruptions prior to the outbreak of the COVID-19 pandemic has been presented by Ivanov et al. [98] (focusing on impact of disruptions and supply chain recovery) and Xu et al. [99] (based on extended bibliometric analysis). The impact of supply chain network disruptions caused by the global spread of COVID-19 has been evaluated by many researchers around the world. An evaluation of the published research coinciding with the spread and right after the subsiding of the pandemic has been presented by Katsaliaki et al. [100] (involving modeling approaches and application of information technology tools), Rinaldi et al. [101] (considering quantitative models), and Novoszel and Wakolbinger [102] (taking into account both quantitative studies and qualitative content, and conducting bibliometric assessment).

Various authors have evaluated supply chain network disruptions and their impact on the inventory management strategies employed for achieving a predefined or target service level over the years. A brief summary of this evaluation for the duration 2001-2023 relevant to the current research work is presented below.

Chen and Krass [11] have investigated inventory models in which the stock-out cost is replaced by a minimum service level constraint requiring that a certain service level be met during each review period. The research work focuses on inventory control models that aim to balance the trade off between inventory costs and customer service levels. It examines various mathematical models and optimization techniques used to determine optimal inventory policies under minimal service level constraints. The research study discusses the concept of service level, which represents the probability of meeting customer demand during a specified time frame. It emphasizes the need to define a minimum acceptable service level to ensure customer satisfaction and avoid potential stock-outs.

The research work further explores different inventory control strategies, such as periodic review and continuous review systems, and evaluates their performance in meeting service level constraints. It also considers factors such as demand variability, lead time variability, and cost structures in the development of inventory models. The authors have highlighted the challenges in implementing minimal service level constraints, including the need for accurate demand forecasting, reliable lead time estimation, and effective inventory management techniques. They have discussed the implications of these constraints on inventory costs, order quantities, and reorder points. Hwang [103] has optimized the performance of a logistics system subject to required service levels both in the number of warehouses or distribution centers and vehicle routing schedule.

TABLE 2.3: Relevant literature for sustainable and resilient supplier selection and order allocation

Research Study	**EC**	**E$_n$C**	**SC**	**RC**	**SS Technique(s)**	**OA Technique(s)**	**Application Case Study**
Rajesh and Ravi [87]				✓	GRA, AHP, ANP		Electronics devices manufacturing industry
Sen et al. [104]		✓		✓	TODIM		Numerical problem
Amindoust [105]	✓	✓	✓	✓	FIS, Assurance Region (AR) DEA		Alloy manufacturing industry
Jabbarzadeh et al. [106]	✓	✓	✓	✓	Stochastic bi-objective optimization		Plastic goods manufacturing industry
Mohammed et al. [94]	✓	✓		✓	Fuzzy AHP, TOPSIS	Fuzzy multi-objective programming	Food supply chain
Hosseini et al. [12]	✓			✓		Stochastic bi-objective mixed-integer programming	Numerical problem

Yavari and Zaker [95]	✓	✓		✓	Mixed-integer linear programming		Dairy supply chain
Fallahpour et al. [107]	✓	✓	✓	✓	Fuzzy DEMATEL, Fuzzy ANP, Fuzzy BWM, FIS		Palm oil industry
Fazlollahtabar and Kazemitash [108]	✓	✓	✓	✓	Authors' custom technique, DEA		Electrical equipment manufacturing industry
Mahmoudi et al. [109]		✓		✓	Fuzzy OPA		Numerical problem
Proposed framework	✓	✓	✓	✓	Fuzzy AHP, Fuzzy TOPSIS	Fuzzy multi-objective mixed-integer nonlinear programming	Pharmaceutical industry

The research work addresses the challenge of designing a supply chain logistics system that meets customer service level requirements while minimizing cost and maximizing efficiency. It emphasizes the need to strike a balance between service level objectives and operational constraints and presents a framework to achieve this goal. The proposed framework incorporates several key elements. First, it considers the design of the supply chain network, including the selection of distribution centers and the allocation of inventory. The aim is to optimize the network configuration to ensure timely and reliable deliveries that meet customer expectations. Secondly, the research study incorporates inventory management strategies, such as safety stock levels and order policies, to support the desired service level. By accurately managing inventory, the logistics system can effectively respond to customer demands and maintain high service levels. Furthermore, the research work highlights the importance of transportation management in achieving service level objectives. It considers factors such as transportation mode selection, routing, and scheduling to optimize delivery times and minimize delays. The authors have emphasized the integration of information technology and real-time data to enable visibility and coordination across the supply chain. By leveraging technology, companies can monitor and manage the logistics system more effectively, leading to improved service levels.

A single-period two-stage service-constrained supply chain under the condition of variations in demand forecast has been evaluated by Sethi et al. [110]. The authors have determined the optimal ordering policy under service constraints and incorporated the effects of forecast quality in their analysis. The research work recognizes that maintaining a satisfactory service level is crucial for customer satisfaction and overall supply chain performance. The authors have further discussed strategies for integrating information from various sources, including customers, suppliers, and internal systems, to improve supply chain responsiveness and service level performance. The research study highlights the benefits of the information updated supply chain, including improved customer service, reduced stock-outs, enhanced supply chain visibility, and better decision making capabilities.

Lee et al. [111] have presented a continuous review inventory model that takes into account lead time demand along with controllable exponential backorder rate.

The authors have proposed two computational algorithms for determining optimal values of order quantity and lead time. The research work attempts to solve an inventory management problem with a service level constraint, the lead time demand following a mixture of distributions, and the backorder rate modeled and controlled using a negative exponential distribution. The research study recognizes the challenge of simultaneously considering multiple factors that affect inventory management decisions and offer the two computational algorithms as decision making aids in determining appropriate inventory policies that meet service level requirements under operational restrictions.

A transshipment policy in which service level has been used as a deciding factor for calculating the quantity for lateral transshipment has been proposed by Lee et al. [112]. The authors have evaluated their model using a two echelon supply chain network and observed that their proposed policy effectively responds to changes in demand, ordering cost, and penalty cost. The research work recognizes the importance of maintaining high service levels to meet customers' demand and improve overall supply chain performance. It addresses the challenge of achieving this objective while minimizing inventory costs and avoiding stock-outs. The research study presents an effective algorithm for determining when and how much inventory should be transshipped between locations. The algorithm considers factors such as demand patterns, lead times, and inventory levels at different locations. Furthermore, the research work emphasizes the importance of information sharing and collaboration among supply chain partners for successful lateral transshipment implementation.

Farahani and Elahipanah [113] have developed a bi-objective mathematical model for a supply chain network operating on just-in-time distribution paradigm. The research work recognizes the significance of cost optimization and service level management in a just-in-time distribution system that aims to minimize inventory holding cost while ensuring timely delivery and customer satisfaction, and presents GA as a powerful optimization technique to find the optimal solution to this type of complex problems. The research study describes the formulation of the optimization problem, considering factors such as transportation costs, inventory costs, customer service level, and order fulfillment constraints. It explains how GA is utilized to search for the best combination of variables that minimizes total cost while meeting service level requirements. Additionally, the GA approach allows for flexibility and adaptability in addressing changing conditions and requirements within the supply chain. Application case studies have also been presented in this research work to demonstrate the effectiveness of the GA approach and to showcase how the algorithm can generate near optimal solutions and improve supply chain performance.

An inventory management methodology to handle variable demand requirements during supply chain network operations has been presented by Jeffery et al. [114]. The proposed methodology can be used to determine a near optimal value of customer service level from the supplier's perspective. The methodology has been implemented using data from the semiconductor industry. The authors acknowledge that providing higher levels of customer service often leads to increased customer satisfaction, loyalty, and potentially higher sales. However, they also recognize that higher service levels come with additional costs, such as inventory holding costs, order processing expenses, and transportation costs. The research work proposes a framework for determining a cost effective customer service level by considering various factors. These factors include customer demand patterns, service level requirements, costs associated with different service levels, and the impact of service levels on customer satisfaction and revenue. The authors suggest that organizations should conduct a thorough analysis of their customer base, including understanding customer preferences, needs, and behaviors. By segmenting customers based on their value and demand patterns, organizations can tailor their service levels to different customer groups, ensuring a more efficient allocation of resources. The authors have emphasized the importance of using mathematical models and optimization techniques to find the optimal balance between customer service and costs.

Yang et al. [115] have proposed a game theory based model of a supply chain network comprising of a single supplier and two risk-averse distributors based on economic order quantity production-inventory policy using price, service level, and lot size as the decision or evaluation criteria. The research study recognizes the importance of considering retailers' risk aversion in supply chain decision making. It acknowledges that risk-averse retailers are more cautious in their decision making and tend to prioritize factors such as profit stability and inventory risk. The research work examines the interplay between cost, service level, and order lot size decisions in a supply chain context. It explores the impact of risk aversion on these decisions and their implications for practitioners. The findings suggest that risk-averse retailers tend to set higher prices and target lower service levels to mitigate potential losses and stabilize their profits. They also prefer smaller lot sizes to reduce inventory risk and avoid excessive stock holding. The authors emphasize that these decisions have implications for the overall performance of the supply chain and discuss how higher prices and lower service levels can impact customer demand, market share, and overall profitability. The research study also highlights the trade offs between risk reduction and customer satisfaction in supply chain decision making. It offers insights into the coordination mechanisms that can improve supply chain performance in the presence of risk-averse retailers and suggests strategies such as revenue sharing contracts, quantity flexibility contracts, and risk sharing agreements to align the interests of the supply chain partners and promote overall supply chain efficiency.

Schmitt [116] has presented a model for a multi-level supply chain network susceptible to disruptions. The numerical analysis carried out to demonstrate the model has revealed that strategic placement of proactive inventory to cover short term disruptions or the beginning of long term disruptions, and using reactive backup practices to enable supply chain recovery after extended or permanent disruptions can lead to significant service level improvements. The research work explores different strategies to mitigate the impact of disruptions and to ensure satisfactory customer service. It investigates various strategies that can be employed at different echelons of the supply chain network to protect customer service level. These strategies include inventory positioning, safety stock allocation, order rescheduling, and collaboration between supply chain partners. The authors have discussed the benefits and limitations of each strategy and analyzed their effectiveness in mitigating the impact of disruptions on customer service level. They have considered factors such as lead time, demand variability, and disruption probability in evaluating the performance of these strategies.

A stochastic mathematical formulation for designing a multi-product supply chain network that takes into account both supply-side and demand-side uncertainty simultaneously has been developed by Baghalian et al. [117]. The mathematical model proposed in this research work considers extra and shortage costs in the retailing facilities to achieve a predetermined value of service level for the customers. The mathematical formulation has been illustrated using a numerical example from the agri-food industry. The research work recognizes that supply chain disruptions and demand uncertainties can significantly impact the performance and service levels of supply chain networks. Therefore, it aims to develop a robust network design that can withstand these challenges and ensure customer satisfaction. The research study utilizes mathematical modeling and optimization techniques to design a resilient supply chain network. It considers various factors such as facility location, transportation routes, inventory placement, and capacity allocation. The objective is to minimize costs while maximizing service levels under different disruption scenarios and demand variations. To achieve robustness, the model incorporates different levels of service and develops contingency plans to mitigate the impact of disruptions. It considers backup facilities, alternative transportation routes, and inventory buffers to enhance the network's ability to meet customers' demand during disruptions or fluctuations in demand. The research work provides a real-life case study to demonstrate the application and effectiveness of the proposed approach.

Uthayakumar and Priyan [118] have presented an inventory model for a pharmaceutical manufacturer and a hospital supply chain that integrates continuous review with production and distribution of medical supplies. The model has been demonstrated using a numerical example to determine optimal values of order lot size, lead time, and delivery rate for achieving hospital service level targets with minimum cost for the supply chain network. The research work takes into account the unique challenges in the pharmaceutical supply chain, including product perishability, regulatory requirements, demand uncertainty, and the need for efficient inventory management. It presents optimization models for both pharmaceutical companies and hospitals. For pharmaceutical companies, the research study explores inventory management strategies that consider production capacities, lead times, demand variability, and service level requirements. The models aim to minimize inventory holding costs and stock-outs while meeting customer demand and ensuring product availability. In the context of hospitals, the research work addresses the challenges of managing pharmaceutical inventory with fluctuating patient demand and limited storage space. It proposes models that optimize order quantities and reorder points based on demand patterns, lead times, and service level obligations. The goal is to reduce inventory holding costs, minimize stock-outs, and maintain an appropriate level of pharmaceutical supplies for patient care. The authors have also discussed the integration of information technology and advanced analytics in pharmaceutical supply chain and inventory management.

The uncertainty introduced in the supply chain network due to the variation in the service rates of the manufacturing units constituting the supply chain has been evaluated by Almaktoom et al. [119]. The authors have presented a robust design optimization methodology that takes into account production uncertainty and transportation delays in order to satisfy service level rate requirements of the overall network and to ensure its robustness. The research study focuses on the complexity of modern supply chain networks, which involve multiple interconnected entities such as suppliers, manufacturers, distributors, and retailers. It highlights that disruptions at any point in the network can have cascading effects on the overall system performance and service level. To address this issue, the authors propose an approach to assess and enhance the robustness of system service level within a supply chain network. The approach involves analyzing the vulnerabilities and dependencies within the network, identifying critical nodes and links, and evaluating the potential impact of disruptions on the service level. The research work suggests employing mathematical modeling, simulation techniques, and data analysis to quantify the effects of disruptions and to evaluate the resilience performance of the supply chain network.

Sawik [120] has analyzed the SS-OA problem in the presence of disruption risks from the perspective of single or multiple sourcing strategies. The mathematical model proposed optimizes cost and service level and the risk-averse solutions that optimize the worst case performance of the supply chain network under disruption risks have been compared for the two sourcing strategies and the two objective functions. The research work considers factors such as supplier reliability, lead time variability, and disruption probability. By comparing the results of the optimization model, the authors have evaluated the performance of single sourcing and multiple sourcing strategies. They investigate how each strategy impacts total cost and service level particularly in the presence of disruption risks. The research study further discusses the findings related to the trade offs between cost and service level in both sourcing strategies. It explores scenarios where one strategy outperforms the other based on specific cost and service level objectives. The analysis provides insights into the benefits and limitations of each strategy in managing supply chain disruption risks. The research work highlights that organizations need to carefully evaluate their specific circumstances and requirements when choosing between single sourcing and multiple sourcing strategies. Factors such as product criticality, supplier capability, and risk tolerance should be considered in this regard.

A decision making problem of a fair optimization between cost and service level in the presence of supply chain network disruption risks has been presented by Sawik [121]. The problem has been formulated as a combinatorial stochastic optimization problem and it has been implemented using a numerical case study. The research work recognizes that disruptions in the supply chain can lead to increased costs and reduced customer service level. It emphasizes the need for a fair and balanced approach to optimization that takes into account both cost and service level objectives. The author presents a mathematical model that incorporates disruption risks and aims to optimize the trade off between cost and customer service level. The model accounts for various factors such as supplier reliability, lead time variability, and disruption probability. One key aspect of the model is the introduction of a fairness constraint that ensures an equitable distribution of costs and service level impacts among different parties in the supply chain network. The fairness constraint helps prevent any single entity from disproportionately bearing the negative consequences of disruptions. The findings of the research study highlight that under the conditions of increasing disruption probability or reduced service

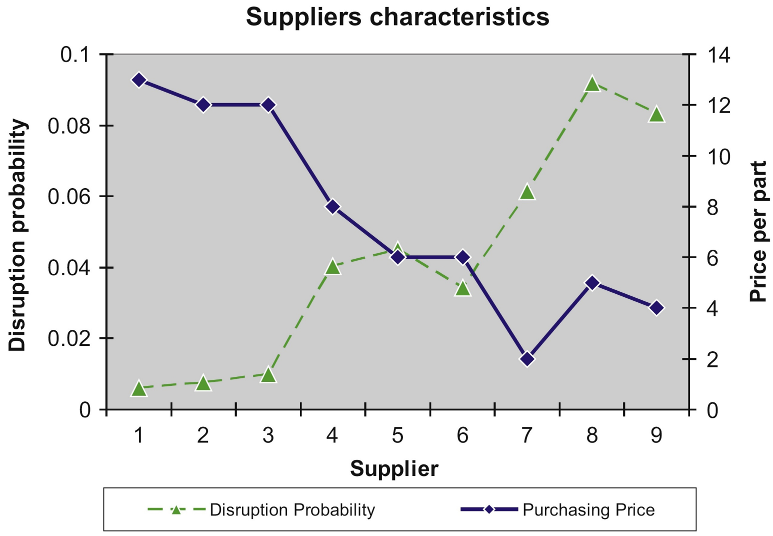


FIGURE 2.6: Disruption probability vs. product price (from [121], with permission)

level, for the minimum cost objective, the cheapest supplier is usually selected, whereas for the maximum service level objective, a subset of most expensive and most reliable suppliers will be chosen. The equitably efficient supply portfolio will normally combine the most reliable and the cheapest suppliers under these conditions (Fig. 2.6).

Radasanu [122] has evaluated the link between safety stock and service level and the design and execution of a successful inventory management policy. In this research work, a statistical model has also been proposed for calculating the quantity of safety stock that enables prevention of a stock-out situation with respect to a predefined customer service level. The research work recognizes the importance of inventory management in meeting customer demand while maintaining adequate service level. It emphasizes the need to strike a balance between inventory costs and customer service objectives. The author has discussed that service level is influenced by various factors i.e. lead time, demand variability, inventory availability etc. and highlighted the role of safety stock in improving service level by ensuring that stock-outs are minimized and customer demand is met consistently. The research work further explores different approaches and mathematical models used in determining the appropriate level of safety stock. It discusses techniques such as the reorder point model, probabilistic models, and optimization methods to calculate safety stock quantities based on desired service levels and other relevant factors. The research study emphasizes the need for organizations to consider both costs and service level requirements when making decisions regarding inventory management. It highlights the trade offs between carrying excess inventory (increasing service level but incurring higher costs) and carrying insufficient inventory (risking stock-outs and lower service levels). Effective inventory management practices including appropriate safety stock levels contribute to improved customer satisfaction, reduced stock-outs, and overall supply chain performance.

A two echelon supply chain network with a single manufacturer and two independent retailers where the manufacturer is facing disruptions while the retailers compete on price and service level has been analyzed by Giri and Sarkar [123]. The supply chain system has been modeled as a manufacturer-Stackelberg game and a numerical case study has been employed to assess the impact of disruptions on the equilibrium behavior and performance of the supply chain network. The researchers consider a scenario where a disruption in production occurs, leading to limited supply from the manufacturer. The retailers compete with each other based on both price and service level. The objective is to find a coordination mechanism that minimizes the total cost of the system and ensures a fair distribution of profits among the participants. To address this problem, the study proposes a contract framework that encourages cooperation between the manufacturer and retailers.

The contract includes a wholesale price, an allocation rule, and a buyback mechanism. The allocation rule determines the proportion of supply allocated to each retailer while the buyback mechanism enables the return of unsold goods to the manufacturer. The authors have analyzed the optimal contract parameters and find that the coordination mechanism significantly improves the performance of the supply chain. It leads to lower total costs, higher profits for the manufacturer and the two retailers, and a fair distribution of profits. The research work also highlights the importance of considering both price and service level competition when designing coordination mechanisms in disrupted supply chains. Adenso-Diaz et al. [124] have developed a metric for evaluating the robustness of a supply chain network under the impact of successive collapse of its transportation links.

The analysis of the results of the numerical experiments conducted to evaluate the performance of the metric shows that flow complexity and service level after disruptions are two of the most significant factors affecting supply chain network robustness. The research work discusses various methodologies and models that can be used to simulate and evaluate the effects of link failures on the supply chain network. This analysis includes estimating the impact on key performance indicators like delivery time, cost, or customer satisfaction. Additionally, the authors emphasize the need for proactive measures to enhance supply chain robustness. They have suggested strategies like diversifying suppliers, establishing redundancies, and implementing contingency plans to minimize the negative impact of link failures.

A supply chain comprised of one supplier and one retailer in which demand uncertainty has been addressed using service level constraint and put options has been evaluated by Chen et al. [125]. It has been observed that during the periods of greater demand variability, with put options the retailer usually offers higher service level. Put options provide the right to sell assets at a predetermined price, offering protection against potential losses caused by price fluctuations or disruptions. The research work has presented an optimization approach that incorporates put options and service level constraints into supply chain risk management. It aims to identify optimal strategies that balance risk mitigation and customer service. Case studies and practical applications have been included in the research work to illustrate the implementation and effectiveness of the proposed approach.

Yan et al. [126] have evaluated the efficacy of multi-channel ordering decisions for a two echelon supply chain network in order to identify the best possible price and logistic service level combinations. The models presented in this research work employ Stackelberg game and consumer utility function to analyze the profits of both the retailer and the manufacturer for arriving at an optimal channel strategy. The research work presents a quantitative model that incorporates various factors, including customer preferences, demand patterns, transportation costs, inventory holding costs, and service level constraints. The model aims to optimize the logistic service level decision in the context of the multi-channel supply chain. Furthermore, the authors have discussed the implications of different logistic service levels on the overall performance of the supply chain. They have examined how varying service levels can impact customer satisfaction, channel revenues, inventory levels, and transportation costs. The findings of the research study indicate that the choice of logistic service level has a notable influence on the multi-channel decision of the supply chain network. It emphasizes the importance of considering factors such as demand variability, customer preferences, and operational capabilities when determining the optimal service level for each channel.

Arana et al. [127] have proposed an optimal supply methodology for improving the service level of a two echelon supply chain network. The proposed methodology has been demonstrated by implementing it based on data collected from the pharmaceutical industry. The research work recognizes the criticality of an efficient and effective pharmaceutical supply chain in ensuring timely availability of medications and health care products. It aims to evaluate the current service level and proposes an optimal policy to enhance the supply chain performance. In order to achieve this goal, various factors impacting the service level i.e. inventory management, transportation means, lead time, and demand patterns etc. have been considered.

The research study employs optimization techniques and mathematical models to identify an optimal policy that can maximize the service level of the pharmaceutical supply chain while minimizing costs and inventory levels. By adopting an approach that considers inventory management, transportation efficiency, and other relevant factors, pharmaceutical firms can achieve better service level performance and meet the health care needs of the population more effectively.

A supply chain network model with demand uncertainty and service level constraints has been presented by Bhuniya et al. [128]. The model has been evaluated using various business strategies with total cost reduction as the primary optimization criteria. The research work develops a mathematical model that takes into account various factors such as demand variability, lead time uncertainty, and inventory management strategy. The model aims to optimize the supply chain network performance by determining the optimal order quantities, reorder points, and safety stock levels that ensure the desired service level is always met. The authors have emphasized the significance of considering service level constraints i.e. desired levels of product availability and customer satisfaction in supply chain decision making. In order to address uncertainty, the research work has employed probabilistic techniques such as stochastic programming and simulation to capture the random variation in demand and lead time. These techniques enable DMs to evaluate and compare different strategies under various uncertainty scenarios while considering factors such as fill rate, backorders, or stock-outs.

Sinha et al. [129] have developed a modeling approach for optimal functionality of a COVID-19 vaccine distribution network subject to lead time disruption risk and service level constraint. In this research work, strategic placement of inventory reserves at critical nodes has been proposed as a remedial measure for addressing any shortcoming to the fulfillment of objective service level in the face of infrastructure limitations.

The research work describes the critical role of efficient vaccine supply chains in combating the COVID-19 pandemic and emphasizes the need to ensure an adequate and timely supply of vaccines to achieve herd immunity. It highlights the unique challenges faced by the DMs in an Indian context such as a large population, diverse geography, and logistical complexities.

The authors propose strategies to enhance the service level in the vaccine supply chain and emphasize the importance of demand forecasting and inventory management to prevent stock-outs thus ensuring a steady supply of vaccines. They also suggest the implementation of distribution network optimization to improve the efficiency of vaccine delivery across different regions.

Furthermore, the research study discusses the significance of collaboration and coordination among stakeholders, including vaccine manufacturers, transportation service providers, health care facilities, and government agencies. It emphasizes the need for information sharing, real-time monitoring, and agile decision making to address supply chain disruptions and ensure the availability of vaccines.

2.6 Discussion

An extensive literature review and discussion concerning supplier selection, order allocation, TBL sustainability, resilience, and supply chain network disruptions has been presented in the preceding sections.

A few observations regarding the broader research area pertaining to sustainable supplier selection seems relevant here. A lack of consistent frameworks for sustainable SS-OA has been observed. Different research studies adopt varying criteria, metrics, and methodologies, making it challenging to compare and generalize findings. There is a need for standardized frameworks that consider all TBL dimensions of sustainability to ensure coherence and comparability across studies. The environmental sustainability dimension receives considerable attention in the literature but there is a relative lack of emphasis on social dimension.

The literature lacks a thorough analysis of the financial implications of SSS-OA as well. While environmental and social considerations are critical, organizations also need to evaluate the financial feasibility and cost-effectiveness of sustainable practices. Lastly, while the literature provides insights into the theoretical aspects of SSS-OA, there is limited discussion on the practical challenges and barriers that organizations face during implementation. Identifying and addressing these implementation challenges would facilitate the successful adoption of sustainable practices.

An objective evaluation of the literature search and analysis presented in the sections 2.2 and 2.3 leads to the critical observation that SSS-OA has been mostly studied separately from resilient SS-OA. In recent times, the emergence and global spread of COVID-19 pandemic has highlighted the limitation of this approach as it is not always the case that a sustainable supplier will be a resilient supplier as well. The performance of such a supplier will mostly be far from ideal under the impact of supply chain network disruptions.

Furthermore, based on the literature review and comparison presented in section 2.4, it is concluded that even if sustainability and resilience have been considered together, resilience sub-criteria have been usually incorporated in the supplier selection process only and rarely in the order allocation part. It has also been noted that resilience sub-criteria considered in many research studies are vague or inadequately defined with limited scope and application e.g. general disruption, general risk etc., which limits their usefulness for evaluating the dynamics of supply chain network operations under the influence of disruption scenarios. The current literature on SRSS-OA lacks application of objective, quantitative MCDM techniques for supplier selection and presents very little effort towards development of detailed mathematical models for order allocation based on combined TBL sustainability and resilience criteria.

In light of the literature survey and discussion presented in section 2.5, it can be concluded that the impact of disruptions on the service level of a supply chain network has been analyzed by many researchers over the years. This analysis however, has been usually carried out without reference to any quantitative measure of the sustainability or resilience performance of the supply chain or any of its components being taken into account.

In addition to the bibliographic review presented in this chapter, an analysis of the extant literature pertaining to SSS-OA available for the duration 2010-21 has been performed with the objective to identify the types of application case studies considered. The summary of the analysis has been included in Fig. 2.7. Besides numerical problems, the main focus of the researchers for the last many years has been the automobile/automotive parts and electrical/electronics goods manufacturing industries, respectively.

In order to address the shortcomings of the extant literature highlighted above, a sustainable and resilient SS-OA methodology has been presented in the following chapter. For implementing this methodology, a multi-phase, multi-period decision support framework has been developed. The effectiveness of the decision support framework has been evaluated by considering the attainment of a predetermined service level by the supply chain as a performance target under the influence of random (probabilistic) and network (topology) disruptions. The order allocation solutions have been compared for both no disruption and disruption

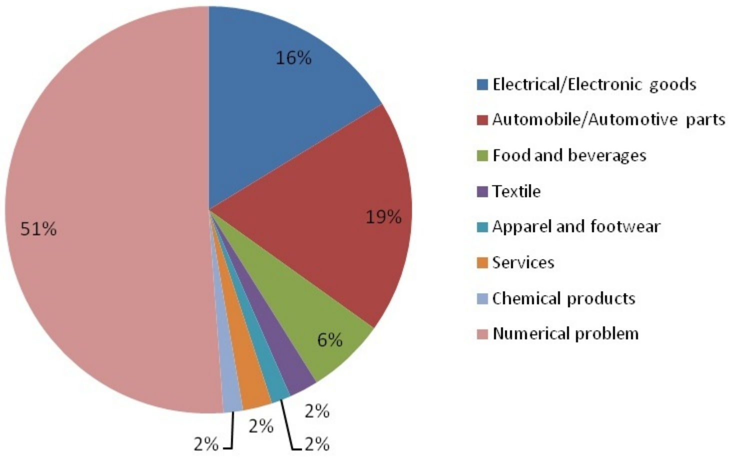


FIGURE 2.7: Industry sector-wise distribution of application case studies

situations with the aim of identifying the best performance configuration for the multi-modal, multi-echelon supply chain network considered for the application case study problem.

Chapter 3

Proposed Methodology

3.1 Introduction

In this research work, a multi-modal, multi-echelon supply chain network consisting of supplier "i", seaport "j", dry port "k", warehouse "l", and customer "c" has been investigated (Fig. 3.1). The suppliers can ship order quantities either through seaport or dry port depending upon their geographical location through various transportation modes "m" at any time period "t".

The inclusion of a dedicated dry port is a distinct feature of this network as it facilitates those suppliers that are located in geographically congruent countries where transportation of order quantities through rail or road is considered more feasible or economical as compared to transportation by sea.

3.2 Proposed Decision Support Framework for SRSS-OA

A multi-phase, multi-period decision support framework has been developed for addressing the issue of sustainable and resilient SS-OA under the influence of disruption scenarios. The detailed schematic of the framework has been presented in Fig. 3.2. The decision support framework has been divided into five phases.

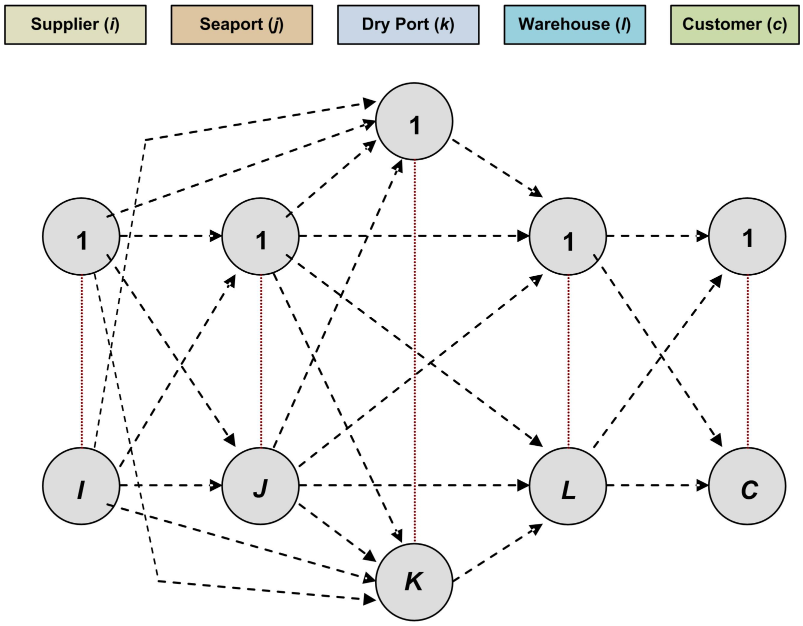


FIGURE 3.1: The supply chain network under evaluation

In the first phase, MCDM techniques fuzzy extended AHP (FE-AHP) and fuzzy TOPSIS (FTOPSIS) have been applied to evaluate potential suppliers based on TBL sustainability and resilience criteria. A fuzzy multi-objective, mixed-integer nonlinear programming (FMOMINLP) mathematical model has been developed in the second phase for optimal order allocation to the selected suppliers. This model has been solved by using a nonlinear solver and an exact algorithm i.e. Augmented ε-Constraint 2 (AUGMECON2) method simultaneously for extracting a candidate list of best solutions.

TOPSIS augmented with objective functions weights determined using Criteria Importance through Intercriteria Correlation (CRITIC) method has been applied in the third phase to rank and select the best solutions. In the fourth phase, the MOMINLP mathematical model has been reconsidered and optimized with respect to supply chain network service level while taking into account multiple random and intentional disruption scenarios.

In order to arrive at the best performance configuration for the network, the impact of the disruption scenarios on the service level of the supply chain has been evaluated and the different solutions have been compared against fixed criteria in the fifth and the last phase of the decision support framework.

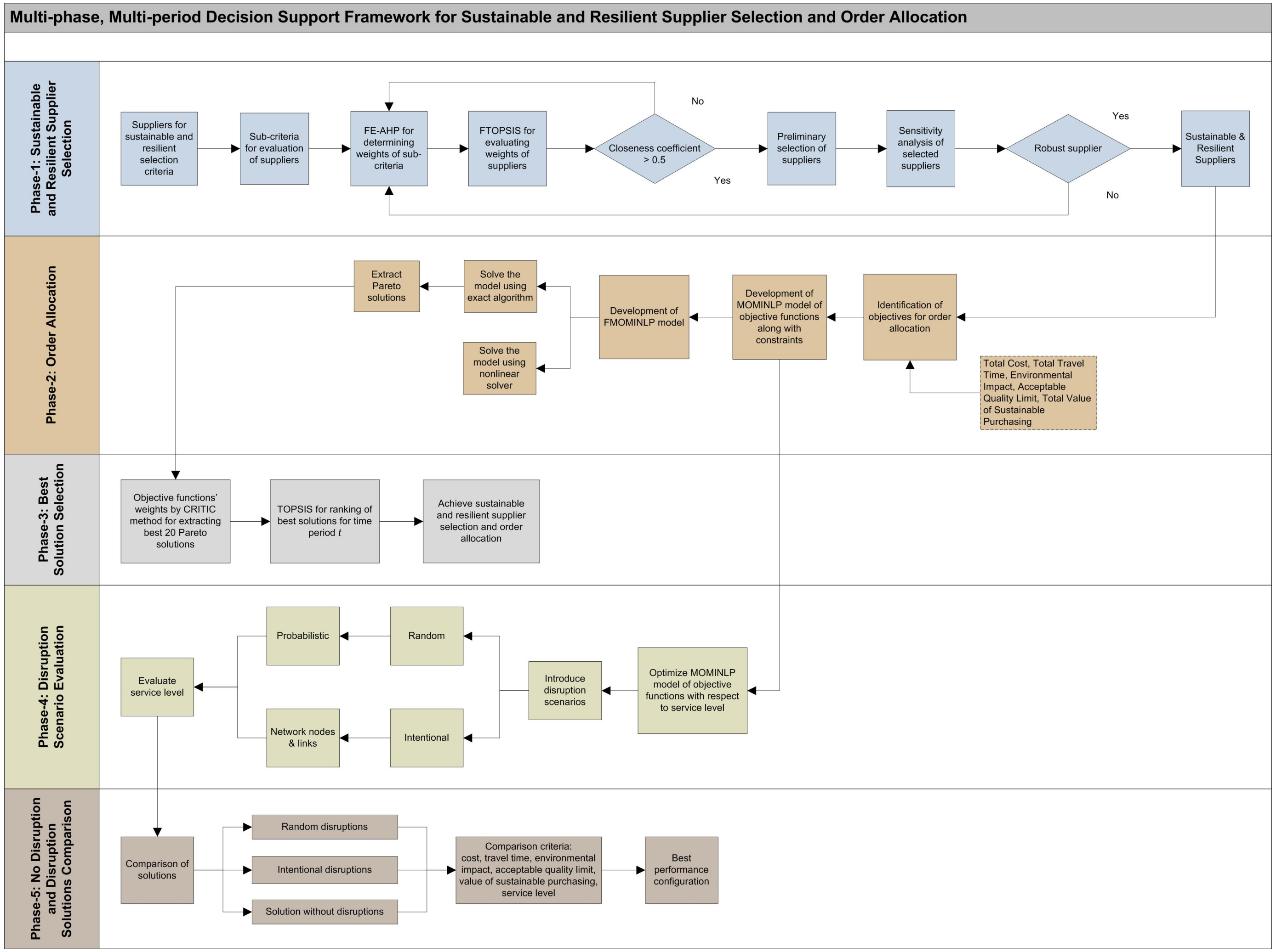


Figure 3.2: The generalized decision support framework for implementation of the proposed methodology

A brief description of the steps involved in each phase of the decision support framework has been included below:

Phase 1: Sustainable and Resilient Supplier Selection

(a) Step-1: Identification of potential suppliers to be evaluated using TBL sustainability and resilience criteria.

(b) Step-2: Identification of sub-criteria for each TBL sustainability and resilience criterion (Table 3.1).

(c) Step-3: Application of FE-AHP for evaluating relative weights of each supplier's selection criteria.

(d) Step-4: Application of FTOPSIS to rank the suppliers.

(e) Step-5: Preliminary selection of suppliers on the basis of defined thresholds of the closeness coefficient.

(f) Step-6: Sensitivity analysis to evaluate the robustness of the selected suppliers (based on the method identified by Forghani et al. [130]).

Phase 2: Order Allocation

(a) Step-7: Identification of objectives for allocating optimal quantities to the potential suppliers. (The objectives are: total cost, total travel time, environmental impact, acceptable quality limit, total value of sustainable purchasing.)

(b) Step-8: Development of MOMINLP mathematical model along with demand, resource, and capacity constraints.

(c) Step-9: Include uncertainty by developing the fuzzy MOMINLP mathematical model.

(d) Step-10: Solve the model using nonlinear solver to determine minimum and maximum values of objective functions.

(e) Step-11: Solve the model using AUGMECON2 and extract Pareto optimal solutions.

Phase 3: Best Solution Selection

(a) Step-12: Use CRITIC method for determining objective functions' weights for extracting best 20 Pareto solutions.

(b) Step-13: Apply TOPSIS for ranking of best solutions for the time period considered.

Phase 4: Disruption Scenario Evaluation

(a) Step-14: Include service level with MOMINLP mathematical model.

(b) Step-15: Introduce random and intentional disruption scenarios.

(c) Step-16: Determine optimal solution for each disruption scenario considered.

Phase 5: Disruption and No Disruption Solution Comparison

(a) Step-17: Compare disruption solutions with no disruption solutions on the basis of pre-identified comparison criteria.

(b) Step-18: Identify best performance configuration for the supply chain network.

3.3 Identification of Supplier Selection Criteria

In order to perform sustainable and resilient supplier selection, a set of 20 sub-criteria has been identified based on the literature review and discussion presented in sections 2.1, 2.2, and 2.4 of the previous chapter. The list of the sub-criteria chosen for use in this research work along with their brief descriptions has been included in Table 3.1.

Table 3.1: Sub-criteria for sustainable and resilient supplier ranking

Criteria	**Sub-criteria**	**Description**
Economic	Product Price	The minimum bidding price received from a supplier [28].
	Payment Terms	The terms and conditions included in the payment schedule [25].
	Product Quality	The inherent characteristics of the product for which the customer is paying for [32].
	Use of Technology	The application of technology solutions for achieving maximum customer satisfaction [39].
	Volume Flexibility	The ability of a supplier to address variations in demand [33].
	Vendor's Reputation	The repute and standing of a supplier among competitors [28].
	Responsiveness	The objective and purposeful response of a supplier aimed at addressing customer's demand in a given timeframe [48].
	Product Mix	The capacity of a supplier to address customer's demand through multiple products [31].
	Past Business	The scale and value of projects carried out by a supplier in the past [29].
Environment	Environmental Management System	The supplier has implemented a recognized environmental management system [47].

	Energy Consumption	The type of conventional or renewable energy resources used in the production facilities of a supplier [40].
	Waste Management System	The type and efficacy of the waste collection, segregation, transportation, and disposal procedures implemented by a supplier [43].
	Innovative Capability	The ability of a supplier to incorporate green design strategies in all stages of the value addition process [45].
Social	Employee Health & Safety	The supplier offers health incentives and implements rigorous standards and procedures for ensuring safety at workplace [49].
	Staff Personal & Technical Development	The availability of opportunities for personal and professional growth offered by a supplier to its employees [60].
	Information Disclosure	The implementation of procedures to curtail any unwanted disclosure of personal or corporate information [40].
Resilience	Robustness	The ability of a supplier to resist or avoid any unwanted change [124].
	Agility	The ability of a supplier to quickly adjust its strategy in order to meet rapidly changing supply chain requirements [95].
	Leanness	The supplier has implemented procedures to eliminate waste across all functions, which can help to reduce lead time [111].
	Flexibility	The ability of a supplier to efficiently respond to market uncertainty [87].

3.4 Supplier Selection Techniques

A brief overview of the supplier selection process and techniques used in this research work has been presented below.

The supplier selection process comprises of two steps. In the first step, the TBL sustainability and resilience criteria and sub-criteria are ranked by determining their relative weights. This step has been implemented using FE-AHP technique. In the second step, the sub-criteria weights calculated in the previous step have been employed in the FTOPSIS technique in order to determine a ranking of the potential suppliers. FST has been used to incorporate the impact of the variation in human judgment in both MCDM techniques. Triangular Fuzzy Numbers (TFNs) a, n, m have been used in this research work to signify DM preferences regarding alternatives, where a, n, m represent the least, average, and maximum values, respectively. The membership function used in the supplier selection analysis has been adapted from Chang [131] and included in Eq. 3.1.

$$V(\widetilde{M}_i \geq \widetilde{M}_j) = \begin{cases} 1 & if\, n_2 \geq n_1 \\ \dfrac{(a_1 - m_2)}{(n_2 - m_2) - (n_1 - a_1)} & otherwise \\ 0 & if\, a_1 \geq m_2 \end{cases} \tag{3.1}$$

where,

$$M_1 = (a_1, n_1, m_1),\ M_2 = (a_2, n_2, m_2)$$

FE-AHP has been used to calculate the weights of TBL sustainability and resilience criteria and sub-criteria in this research work. The linguistic variables (adapted from Chen [132]) that have been used for implementing both MCDM techniques have been included in Tables 3.2 and 3.3, respectively.

A graphical representation of the triangular membership function for evaluation of TBL sustainability and resilience criteria and sub-criteria has been included in Fig. 3.3. FE-AHP has been implemented based on the methodology presented by Wang et al. [133]. The various steps of the implementation process have been included in Fig. 3.4. FTOPSIS has been used to determine the ranking of suppliers based on the values of the sub-criteria weights determined through FE-AHP. The linguistic variables used for implementing the technique have been included in Table 3.3. FTOPSIS has been implemented based on the procedure followed by Gupta and Barua [134]. The various steps of the implementation process have been included in Fig. 3.5.

TABLE 3.2: Linguistic variables used for FE-AHP

Importance of Criteria	
Linguistic Variable	**Fuzzy Number**
Weakly Important (WI)	(0.1, 0.1, 0.3)
Moderately Important (MI)	(0.1, 0.3, 0.5)
Important (I)	(0.3, 0.5, 0.7)
Strongly Important (SI)	(0.5, 0.7, 0.9)
Extremely Important (EI)	(0.7, 0.9, 1)

TABLE 3.3: Linguistic variables used for FTOPSIS

Performance Ranking of Alternatives	
Linguistic Variable	**Fuzzy Number**
Very Low (VL)	(1, 1, 3)
Low (L)	(1, 3, 5)
Medium (M)	(3, 5, 7)
High (H)	(5, 7, 9)
Very High (VH)	(7, 9, 10)

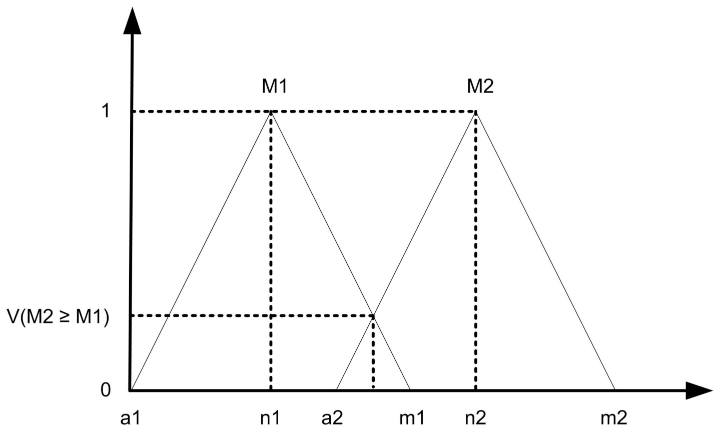


FIGURE 3.3: Membership function for evaluation of criteria and sub-criteria

3.5 Development of Mathematical Model for Order Allocation

The development of the MOMINLP mathematical model has been presented in this section. FST has been applied to incorporate real-world uncertainty in the mathematical model. The objective functions along with the assumptions, sets, parameters, and variables used in the mathematical model have been included below:

Assumptions

(1) The model is a multi-period model. (2) The shipments are considered as less than container load (LCL) shipments. (3) The transfer cost and transfer time can only be applied at the nodes. (4) The custom clearance cost and custom clearance time can only be applied while moving through port. (5) Custom clearance can only take place at one port for a shipment i.e. either at seaport or dry port.

Sets

i=1,2,3,...,I Set of suppliers

j=1,2,3,...,J Set of seaports

k=1,2,3,...,K Set of dry ports

l=1,2,3,...,L Set of warehouses

c=1,2,3,...,C Set of customers

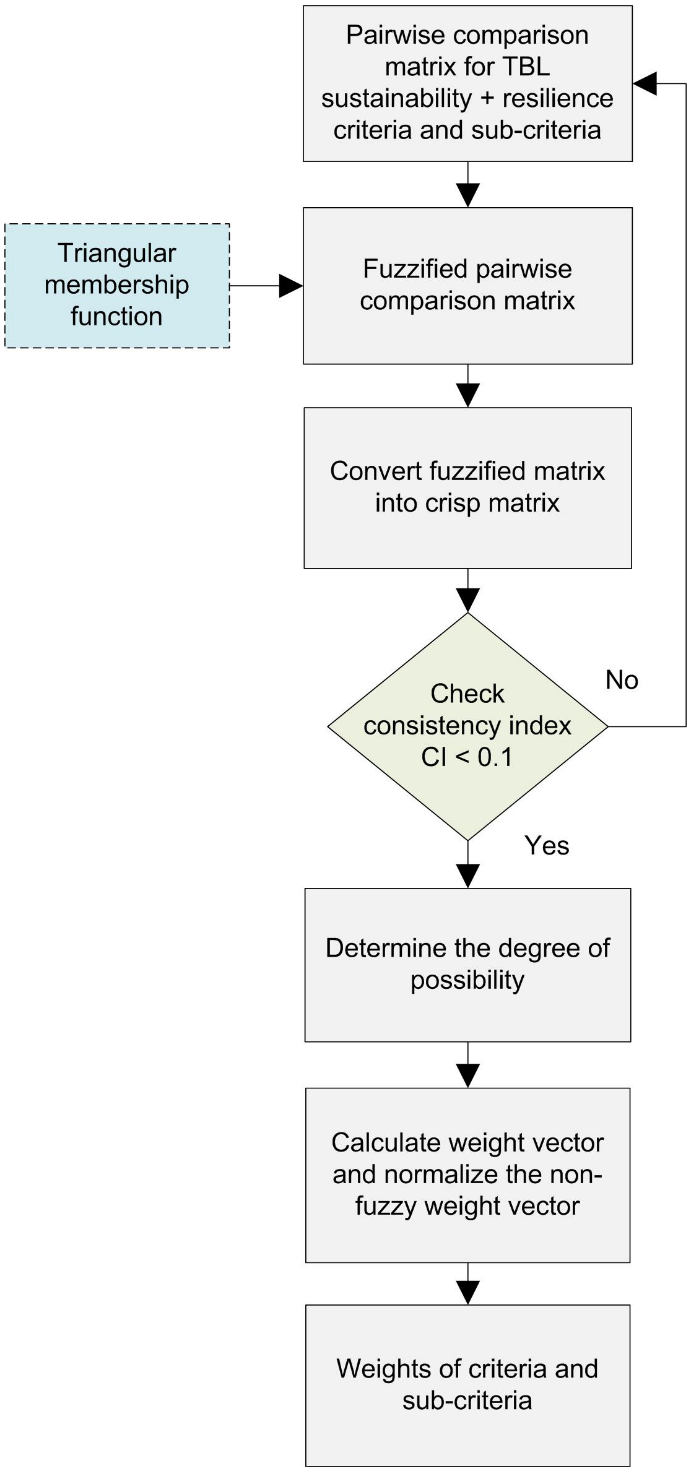


FIGURE 3.4: Flow chart for implementation of FE-AHP

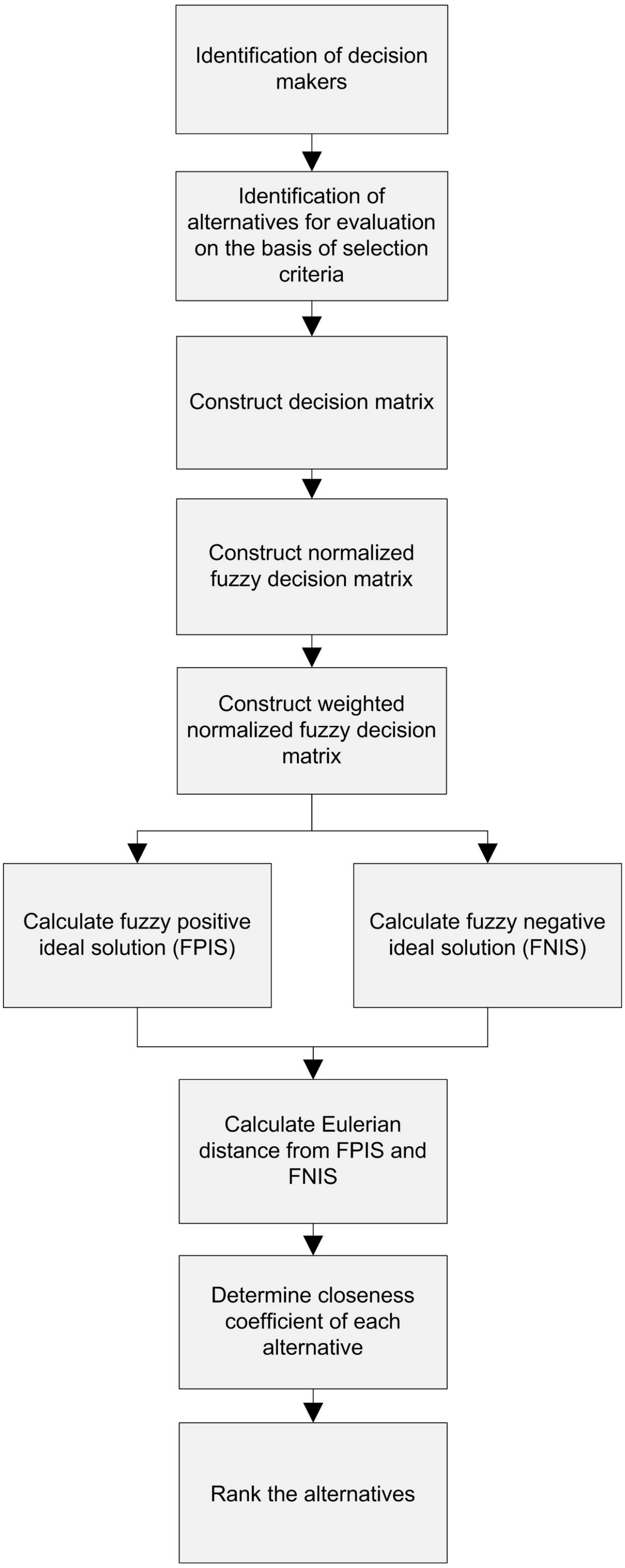


FIGURE 3.5: Flow chart for implementation of FTOPSIS

t=1,2,3,..., T Set of time periods

$m = 1, 2, 3, ..., M$ Set of transportation modes
$n = 1, 2, 3, ..., N$ Set of transportation modes
$\Big\}$ For intermodal transfer decisions

Parameters

C^{p}_{it} = Purchasing cost per kg from supplier i for time period t

O_{it} = Ordering cost incurred by customer for i^{th} supplier for time period t

Ho_t = Inventory holding cost per kg incurred by customer for time period t

TC_{mt} = Transportation cost per km for mode m for time period t

TrC_{mnt} = Transfer cost from mode m to mode n for time period t

CC_{ijt} = Custom clearance cost while moving from supplier i to seaport j for time period t

CC_{ikt} = Custom clearance cost while moving from supplier i to dry port k for time period t

TrT_{mnt} = Transfer time from mode m to mode n for time period t

CCT_{ijt} = Custom clearance time from supplier i to seaport j for time period t

CCT_{ikt} = Custom clearance time from supplier i to dry port k for time period t

d_{ijm} = Distance from supplier i to seaport j through mode m

d_{jlm} = Distance from seaport j to warehouse l through mode m

d_{lcm} = Distance from warehouse l to customer c through mode m

d_{ikm} = Distance from supplier i to dry port k through mode m

d_{klm} = Distance from dry port k to warehouse l through mode m

d_{jkm} = Distance from seaport j to dry port k through mode m

${w_i}^{eco}$ = Weights of economic criteria obtained from fuzzy E-AHP for supplier i

w^{e}_{i} = Weights of environmental criteria obtained from fuzzy E-AHP for supplier i

w^{s}_{i} = Weights of social criteria obtained from fuzzy E-AHP for supplier i

$W^{Economic}_{i}$ = Weights of supplier i from fuzzy TOPSIS for economic criteria

$W^{Environmental}_{i}$ = Weights of supplier i from fuzzy TOPSIS for environmental criteria

W^{Social}_{i} = Weights of supplier i from fuzzy TOPSIS for social criteria

${w_i}^{Risk}$ = Risk weight of supplier i normalized by results of risk expectation value

CO_{2ijmt} = Carbondioxide emissions in gram per km while traveling from supplier i to seaport j through mode m for time period t

CO_{2jlmt} = Carbon dioxide emissions in gram per km while traveling from seaport j to warehouse l through mode m for time period t

CO_{2lcmt} = Carbon dioxide emissions in gram per km while traveling from warehouse l to customer c through mode m for time period t

CO_{2ikmt} = Carbondioxide emissions in gram per km while traveling from supplier i to dryport k through mode m for time period t

CO_{2klmt} = Carbondioxide emissions in gram per km while traveling from dryport k to warehouse l through mode m for time period t

CO_{2jkmt} = Carbondioxide emissions in gram per km while traveling from seaport j to dryport k through mode m for time period t

S_{it} = Maximum capacity of i^{th} supplier for time period t

D_{ct} = Demand of c^{th} customer for time period t

α_{it} = Acceptable quality limit of i^{th} supplier for time period t

$CAPw_{lt}$ = Capacity of l^{th} warehouse for time period t

v_m = Velocity of mode m

Cap_{mt} = Capacity of vehicle used while moving through mode m for time period t

$Cap_{(m=2)t}$ = Maximum capacity of rail for time period t

$Cap_{(m=3)t}$ = Maximum capacity of road for time period t

Integer Variables

X_{ijmt} = Quantity shipped from supplier i to seaport j through mode m for time period t

X_{jlmt} = Quantity shipped from seaport j to warehouse l through mode m for time period t

X_{lcmt} = Quantity shipped from warehouse l to customer c through mode m for time period t

X_{ikmt} = Quantity shipped from supplier i to dryport k through mode m for time period t

X_{klmt} = Quantity shipped from dry port k to warehouse l through mode m for time period t

X_{jkmt} = Quantity shipped from seaport j to dry port k through mode m for time period t

Binary Variables

$$\mathrm{Y}_{it} = \begin{cases} 1 & \text{if supplier } i \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{Z}_{lt} = \begin{cases} 1 & \text{if warehouse } l \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{a}_{jt} = \begin{cases} 1 & \text{if transfer from mode } m \text{ to } n \text{ at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{a}_{kt} = \begin{cases} 1 & \text{if transfer from mode } m \text{ to } n \text{ at node } k \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{a}_{lt} = \begin{cases} 1 & \text{if transfer from mode } m \text{ to } n \text{ at node } l \\ 0 & \text{otherwise} \end{cases}$$

Objective Function 1: Total Cost (TC)

This objective function minimizes the sum of purchasing cost, ordering cost, inventory holding cost, transportation cost, transfer cost, and the custom clearance cost that takes place throughout the supply chain network.

Transfer cost is the labor cost incurred when goods are transferred from one mode of transport to another while custom clearance cost is the cost of preparation and processing of custom entry documents at the port.

In order to incorporate the effects of resilience criteria in order allocation, risk weights for ordering from each supplier are determined and included in the objective function (Appendix B).

It is important to note here that TC will be used as the main or principal objective function during multi-objective optimization being carried out through the chosen solving algorithm in subsequent chapters.

$$
\begin{aligned}
Min \quad \mathrm{TC} = & \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}(C_{it}^{P}X_{ijmt} + C_{it}^{P}X_{ikmt})(1 + w_i^{Risk})Y_{it} + \\
& \sum_{i=1}^{I}\sum_{t=1}^{T}O_{it}Y_{it} + \\
& \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{X_{ijmt} + X_{ikmt}}{2}(Ho_t) + \\
& \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{ijm}\frac{X_{ijmt}}{Cap_{mt}}(1 + w_i^{Risk})Y_{it} + \\
& \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{ikm}\frac{X_{ikmt}}{Cap_{mt}}(1 + w_i^{Risk})Y_{it} + \\
& \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{jkm}\frac{X_{jkmt}}{Cap_{mt}} + \\
& \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{jlm}\frac{X_{jlmt}}{Cap_{mt}} + \\
& \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{klm}\frac{X_{klmt}}{Cap_{mt}} + \\
& \sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}TC_{mt}d_{lcm}\frac{X_{lcmt}}{Cap_{mt}} + \\
& \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrC_{mnt}a_{jt}X_{jkmt} + \\
& \sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrC_{mnt}a_{jt}Z_{lt}X_{jlmt} + \\
& \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrC_{mnt}a_{kt}Z_{lt}X_{klmt} + \\
& \sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrC_{mnt}a_{lt}Z_{lt}X_{lcmt} + \\
& \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}CC_{ijt}X_{ijmt}Y_{it} + \\
& \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}CC_{ikt}X_{ikmt}Y_{it}
\end{aligned}
\tag{3.2}
$$

Objective Function 2: Total Travel Time (TTT)

This objective function minimizes the total travel time from the supplier to the customer. Total travel time is given as a sum of transportation time, transfer time, and custom clearance time. Transfer time is the time required for transfer of goods from one mode of transport to another while custom clearance time refers to the time it takes for the preparation and processing of custom entry documents at the port. The impact of resilience criteria is incorporated by including risk weights for each supplier in this objective function as well (Appendix B).

$$
\begin{aligned}
&Min \quad \text{TTT} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{ijm}X_{ijmt}}{v_m Cap_{mt}}(1+w_i^{Risk})Y_{it}+ \\
&\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{ikm}X_{ikmt}}{v_m Cap_{mt}}(1+w_i^{Risk})Y_{it}+ \\
&\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{jkm}X_{jkmt}}{v_m Cap_{mt}}+ \\
&\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{jlm}X_{jlmt}}{v_m Cap_{mt}}+ \\
&\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{klm}X_{klmt}}{v_m Cap_{mt}}+ \\
&\sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{d_{lcm}X_{lcmt}}{v_m Cap_{mt}}+ \\
&\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrT_{mnt}\frac{X_{jlmt}}{Cap_{mt}}+ \\
&\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrT_{mnt}\frac{X_{klmt}}{Cap_{mt}}+ \\
&\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrT_{mnt}\frac{X_{jkmt}}{Cap_{mt}}+ \\
&\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}TrT_{mnt}\frac{X_{lcmt}}{Cap_{mt}}+ \\
&\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{CCT_{ijt}X_{ijmt}Y_{it}}{Cap_{mt}}+ \\
&\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}\frac{CCT_{ikt}X_{ikmt}Y_{it}}{Cap_{mt}}
\end{aligned}
\tag{3.3}
$$

Objective Function 3: Environmental Impact (EI)

This objective function minimizes the total carbon dioxide emissions throughout the transportation process for all 03 transportation modes i.e. sea, rail, and road.

$$
\begin{gathered}
Min \quad \text{EI} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2ijmt\left[\frac{Xijmt}{Capmt}\right]dijm+ \\
\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2ikmt\left[\frac{Xikmt}{Capmt}\right]dikm + \\
\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2jkmt\left[\frac{Xjkmt}{Capmt}\right]djkm+ \\
\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2jlmt\left[\frac{Xjlmt}{Capmt}\right]djlm+ \\
\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2klmt\left[\frac{Xklmt}{Capmt}\right]dklm + \\
\sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} CO2lcmt\left[\frac{Xlcmt}{Capmt}\right]dlcm
\end{gathered} \tag{3.4}
$$

Objective Function 4: Acceptable Quality Limit (AQL)

This objective function minimizes the acceptable quality limit of the selected suppliers based on different types of defects and their ranges usually employed for order lot size quality assurance.

$$
\begin{gathered}
Min \quad \text{AQL} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} \alpha_{it}X_{ijmt}Y_{it}+ \\
\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} \alpha_{it}X_{ikmt}Y_{it}
\end{gathered} \tag{3.5}
$$

Objective Function 5: Total Value of Sustainable Purchasing (TVSP)

This objective function maximizes the total value of purchased goods by maximizing the economic, environmental, and social criteria weights. The TBL sustainability criteria weights determined using FE-AHP are multiplied by the suppliers' weights calculated using FTOPSIS and the ordered quantity from the supplier.

$$Max \quad \text{TVSP} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\begin{pmatrix} W_i^{Economic} w_i^{eco} X_{ijmt} + \\ W_i^{Environmental} w_i^{e} X_{ijmt} + \\ W_i^{Social} w_i^{s} X_{ijmt} \end{pmatrix} + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}\begin{pmatrix} W_i^{Economic} w_i^{eco} X_{ikmt} + \\ W_i^{Environmental} w_i^{e} X_{ikmt} + \\ W_i^{Social} w_i^{s} X_{ikmt} \end{pmatrix} \tag{3.6}$$

Constraints

The supply constraint represented by Eq. 3.7 ensures that the total order quantity received from the selected suppliers is always less than or equal to the cumulative stated capacity of the suppliers.

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{ijmt} + X_{ikmt}) \leq S_{it}Y_{it} \qquad \forall i \in I \tag{3.7}$$

The demand constraint ensures that the order quantity shipped from the selected suppliers and transferred to the customers after passing through ports and warehouses is in effect equal to the actual demand of the customers. This constraint is represented by Eqs. 3.8, 3.11, and 3.13, respectively.

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{ijmt} + X_{ikmt}) = D_{ct} \qquad \forall j \in J, \forall k \in K \tag{3.8}$$

The equality constraint ensures that the order quantity shipped from the suppliers to the ports is equal to the order quantity that is transferred from the ports to the warehouses and eventually transported to the customers. This constraint has been implemented through Eqs. 3.9, 3.10, and 3.12, respectively.

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{ijmt} + X_{ikmt}) = \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{jlmt} + X_{klmt}) \;\; \forall j \in J, \forall k \in K \tag{3.9}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{jlmt}+X_{klmt})=\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}X_{lcmt} \qquad \forall j\in J,\ \forall k\in K \tag{3.10}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{jlmt}+X_{klmt})=D_{ct} \qquad \forall j\in J, \forall k\in K \tag{3.11}$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}(X_{jlmt}+X_{jkmt}+X_{klmt})=\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}X_{lcmt} \quad \forall j\in J,\ \forall k\in K \tag{3.12}$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T}X_{lcmt}=D_{ct} \qquad \forall l\in L \tag{3.13}$$

The mode capacity constraint ensures that the order quantities transported through various modes should be less than or equal to the maximum capacity of the mode. This constraint has been included in the mathematical model by using Eqs. 3.14-3.24.

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}X_{ij(m=1)t}\le Cap_{(m=1)t} \qquad \forall m\in M \tag{3.14}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}X_{jk(m=2)t}\le Cap_{(m=2)t} \qquad \forall m\in M \tag{3.15}$$

$$\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{t=1}^{T}X_{jk(m=3)t}\le Cap_{(m=3)t} \qquad \forall m\in M \tag{3.16}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T}X_{jl(m=2)t}\le Cap_{(m=2)t} \qquad \forall m\in M \tag{3.17}$$

$$\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T}X_{jl(m=3)t}\le Cap_{(m=3)t} \qquad \forall m\in M \tag{3.18}$$

$$\sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{t=1}^{T}X_{lc(m=2)t}\le Cap_{(m=2)t} \qquad \forall m\in M \tag{3.19}$$

$$\sum_{l=1}^{L}\sum_{c=1}^{C}\sum_{t=1}^{T} X_{lc(m=3)t} \leq Cap_{(m=3)t} \qquad \forall m \in M \tag{3.20}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} X_{ik(m=2)t} \leq Cap_{(m=2)t} \qquad \forall m \in M \tag{3.21}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} X_{ik(m=3)t} \leq Cap_{(m=3)t} \qquad \forall m \in M \tag{3.22}$$

$$\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} X_{kl(m=2)t} \leq Cap_{(m=2)t} \qquad \forall m \in M \tag{3.23}$$

$$\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{t=1}^{T} X_{kl(m=3)t} \leq Cap_{(m=3)t} \qquad \forall m \in M \tag{3.24}$$

The warehouse capacity constraint ensures that the order quantity that is either received or shipped from a warehouse is always less than or equal to the stated storage capacity of the warehouse. This constraint is represented by Eqs. 3.25-3.27.

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{jlmt} \leq CAPw_{lt}Z_{lt} \qquad \forall l \in L \tag{3.25}$$

$$\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{klmt} \leq CAPw_{lt}Z_{lt} \qquad \forall l \in L \tag{3.26}$$

$$\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{lcmt} \leq CAPw_{lt}Z_{lt} \qquad \forall l \in L \tag{3.27}$$

The non-negativity constraint ensures that all order quantities within the supply chain network should always be greater than 0. This constraint has been implemented by Eq. 3.28. The variables that can only take on a binary value are represented by Eq. 3.29.

$$X_{ijmt}, X_{jlmt}, X_{lcmt}, X_{ikmt}, X_{klmt}, X_{jkmt} \geq 0 \qquad \forall i, j, k, l, c, m \tag{3.28}$$

$$Y_{it}\,, Z_{lt}, a_{jt}, a_{kt},\ a_{lt}\ \in \{0, 1\} \qquad \forall i, l \tag{3.29}$$

The constraints should be satisfied with a confidence value ϕ determined by the DMs. As noted earlier, using FST helps to address the uncertainty of human judgment and enables a more precise and objective representation of real-world systems. Based on fuzzy formulation, each objective function corresponds to an equivalent linear membership function, whose value can be calculated by using Eq. 3.30.

$$\mu_b = \begin{cases} 1 & if\ Z_b\ \leq\ Max_b \\ \dfrac{Max_b - Z_b}{Max_b - Min_b} & if\ Min_b \leq Z_b\ \leq\ Max_b \\ 0 & if\ Z_b\ \geq\ Min_b \end{cases} \tag{3.30}$$

In the above equation, Z_b represents the value of the b^{th} objective function, and Max_b and Min_b represent the maximum and minimum values of the b^{th} objective function, respectively [135]. The maximum and minimum values of the membership functions for the objectives have been further illustrated in Fig. 3.6.

Supplier vulnerability is an ever present concern for the DMs. In order to quantify the anticipated risk while evaluating a potential supplier, a risk criteria weight is calculated based on the procedure adopted from Li et al. [136]. In this procedure, for all suppliers being evaluated, DMs' scores for the resilience sub-criteria are combined with the resilience sub-criteria weights determined through a suitable MCDM technique (E-AHP for the purpose of this research work). For each supplier, a risk expectation value is calculated using Eq. 3.31.

$$R_s = \sum_{j=1}^{n} F(C_j) \cdot w_j \tag{3.31}$$

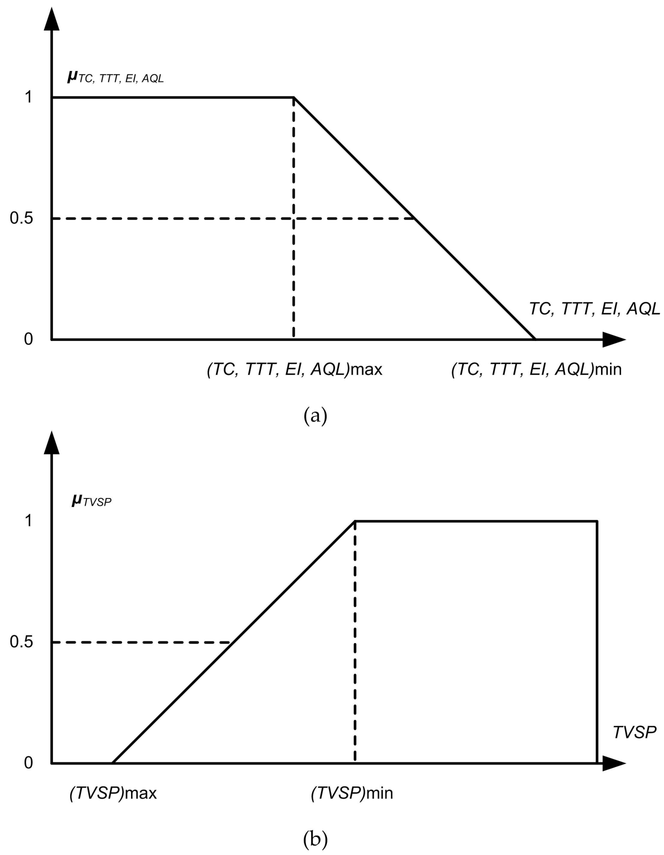


FIGURE 3.6: Membership functions for TC, TTT, EI, AQL, and TVSP

In the above equation, $F(C_j)$ denotes the risk value and w_j is the optimal weight of the resilience sub-criterion C_j, respectively. In the next step, a risk threshold α_R is considered based on the expected risk-bearing capacity of the supplier and the risk preference of the DM. Risk expectation values of all suppliers being evaluated are determined using Eq. 3.31 and compared with α_R. Only those R_s values are retained that fall below DM specified risk threshold and are re-labeled as $R^{'}{}_{s}$. The normalized risk weight ${w_i}^{Risk}$ for each alternative supplier can then be calculated using Eq. 3.32.

$$w_i^{Risk} = \frac{R'_s}{\sum\limits_{i=1}^{I} R'_s} \tag{3.32}$$

The risk weights calculated using the procedure outlined above are applied in those sections of the MOMINLP mathematical model that deal with total cost and total travel time in order to incorporate resilience in the order allocation part of the SRSS-OA problem presented in this research work.

3.6 Solving Algorithm for Order Allocation

AUGMECON2 has been used for solving the fuzzified MOMINLP mathematical model [137]. This solving algorithm is an improved version of the ε-Constraint method proposed by Mavrotas [138]. AUGMECON2 provides exact Pareto set and it is more suitable for solving multi-objective, mixed-integer, non-linear optimization problems. Even when compared with the recent developments of AUGMECON i.e. Robust Augmented ε-Constraint (AUGMECON-R) or the Python Framework for Augmented ε-Constraint (AUGMECON-Py), which are at present being only applied to linear programming problems, AUGMECON2 finds wider application for being considered a tested and established version of the ε-Constraint method [139, 140]. This method transforms a multi-objective problem into a mono-objective problem by considering one of the objectives as the main or principal objective while treating other objectives as constraints subject to certain ε values. The algorithm introduces slack variables at each iteration to adequately address and handle the complexities of discrete variables and non-convex problems. A generic mathematical model of the method is given by Eq. 3.33.

$$max\left(f_1(x) + eps\left(\frac{S_2}{r_2} + \left((10-1)\frac{S_3}{r_3}\right) + ... + \left(10-(n-2)\frac{S_n}{r_n}\right)\right)\right) \tag{3.33}$$

subject to,

$$f_2(x) - S_2 = \varepsilon_2$$
$$f_3(x) - S_3 = \varepsilon_3$$
$$...$$
$$f_n(x) - S_n = \varepsilon_n$$

where, ε_2, ε_3, ..., ε_n are the right-hand side values for each objective function, S_2, S_3, ..., S_n are the slack variables, r_2, r_3, ..., r_n are the ranges of n objective functions, and $eps \in [10^{-6}, 10^{-3}]$. In order to generate exact Pareto sets, AUGMECON2 facilitates lexicographic optimization of objective functions f_2, f_3, ..., f_n. The mathematical model is transformed as presented below to generate the Pareto optimal solutions. For the purpose of this research work, TC has been considered as the main objective function as represented by Eq. 3.34.

$$Min\,Z = Min\,TC \tag{3.34}$$

subject to Eqs. 3.7-3.29, and:

$$\begin{aligned}
&Min\,TTT \leq \varepsilon_2 \\
&[Min\,TTT]^{\min} \leq \varepsilon_2 \leq [Min\,TTT]^{\max} \\
&Min\,EI \leq \varepsilon_3 \\
&[Min\,EI]^{\min} \leq \varepsilon_3 \leq [Min\,EI]^{\max} \\
&Min\,AQL \leq \varepsilon_4 \\
&[Min\,AQL]^{\min} \leq \varepsilon_4 \leq [Min\,AQL]^{\max} \\
&Max\,TVSP \leq \varepsilon_5 \\
&[Max\,TVSP]^{\min} \leq \varepsilon_5 \leq [Max\,TVSP]^{\max}
\end{aligned}$$

A generalized graphical representation of the AUGMECON2 method has been included in Fig. 3.7.

3.7 Selection of Best Pareto Optimal Solution

The large number of optimal solutions generated by the solving algorithm necessitates that an analytical approach must be adopted for identifying and selecting the best solution.

The CRITIC method has been used to calculate objective functions weights in order to select the best 20 Pareto solutions generated using AUGMECON2 [141]. Four best solutions for each confidence value ϕ are determined.

This is followed by TOPSIS for ranking and identification of the best Pareto optimal solution for each time period t. A graphical representation of the procedure implemented for selection of the best Pareto solution has been included in Fig. 3.8.

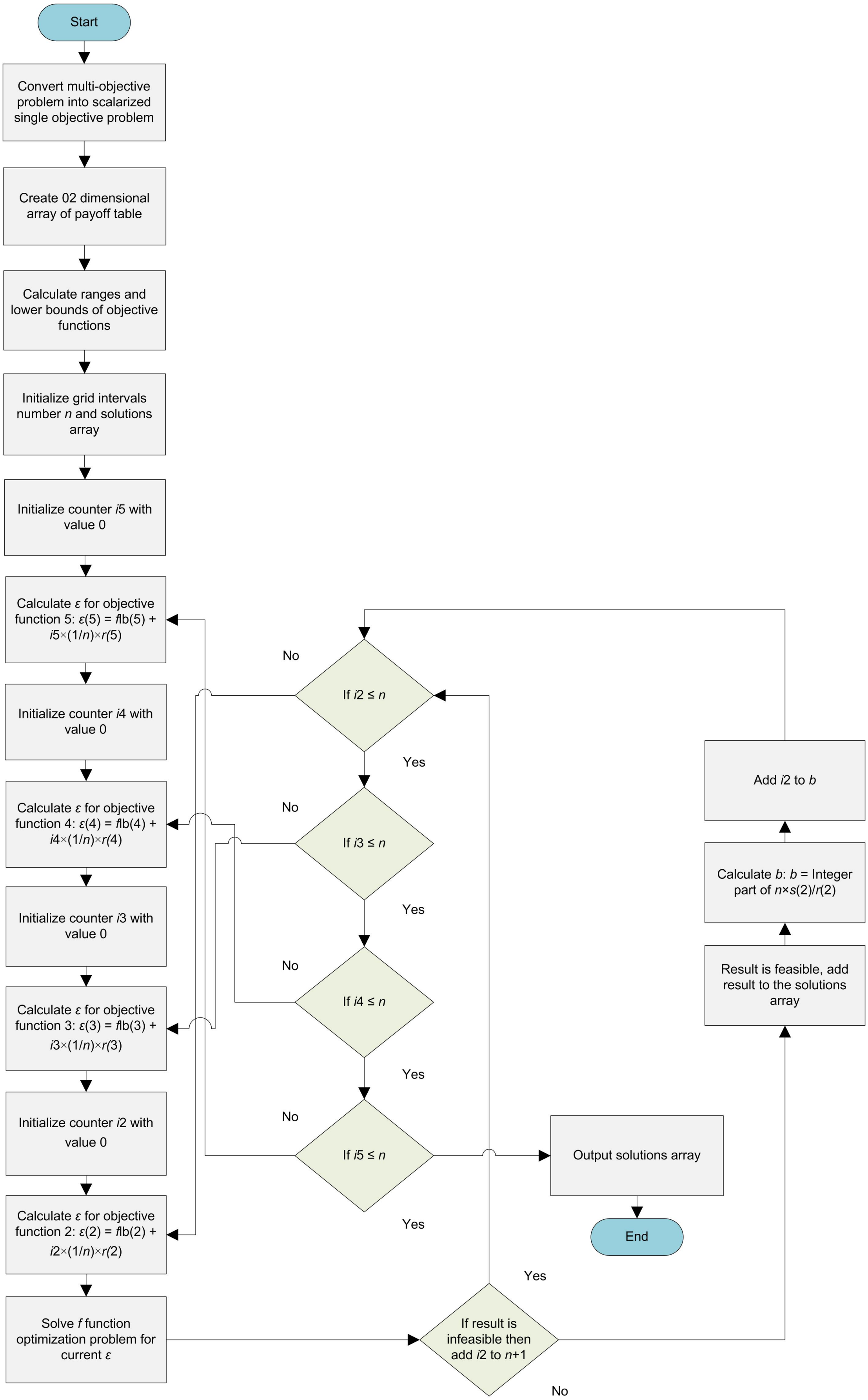


FIGURE 3.7: Flowchart of the AUGMECON2 method

3.8 Evaluation of Disruption Scenarios

The performance of the proposed decision support framework has been evaluated under the influence of multiple types of disruption scenarios and a detailed analysis has been included in Chapter 5.

This evaluation takes into account two types of disruptions i.e. random disruptions that are probabilistic in nature and intentional disruptions that are associated with the topology of the supply chain network.

A procedure has been presented that evaluates the impact of demand uncertainty on the target service level of a supply chain network as specified by the DMs.

Probabilistic demand can give rise to lead time disruptions and in the absence of careful planning such disruptions usually lead to stock-out situations. A quantitative metric termed Supply Chain Index (SCI) developed by Plaganyi et al. [142] for identifying key nodes and links within a supply chain network has been implemented followed by a systematic disabling of certain nodes in order to evaluate the impact of these so called intentional knockout actions on the performance of the overall network measured in terms of predefined comparison criteria.

3.9 Conclusion

In order to demonstrate the utility and potential of the proposed decision support framework in carrying out SRSS-OA under the influence of multiple types of disruption scenarios, it has been implemented using data from the pharmaceutical industry.

The MCDM techniques FE-AHP and FTOPSIS have been implemented using MS Excel (2021) while Python 3.7 has been used for solving the FMOMINLP mathematical model. Both software packages were run using a Core i5/2.5 GHz/8.0 GB RAM personal computer. The detailed results and their analysis has been presented in the following chapter.

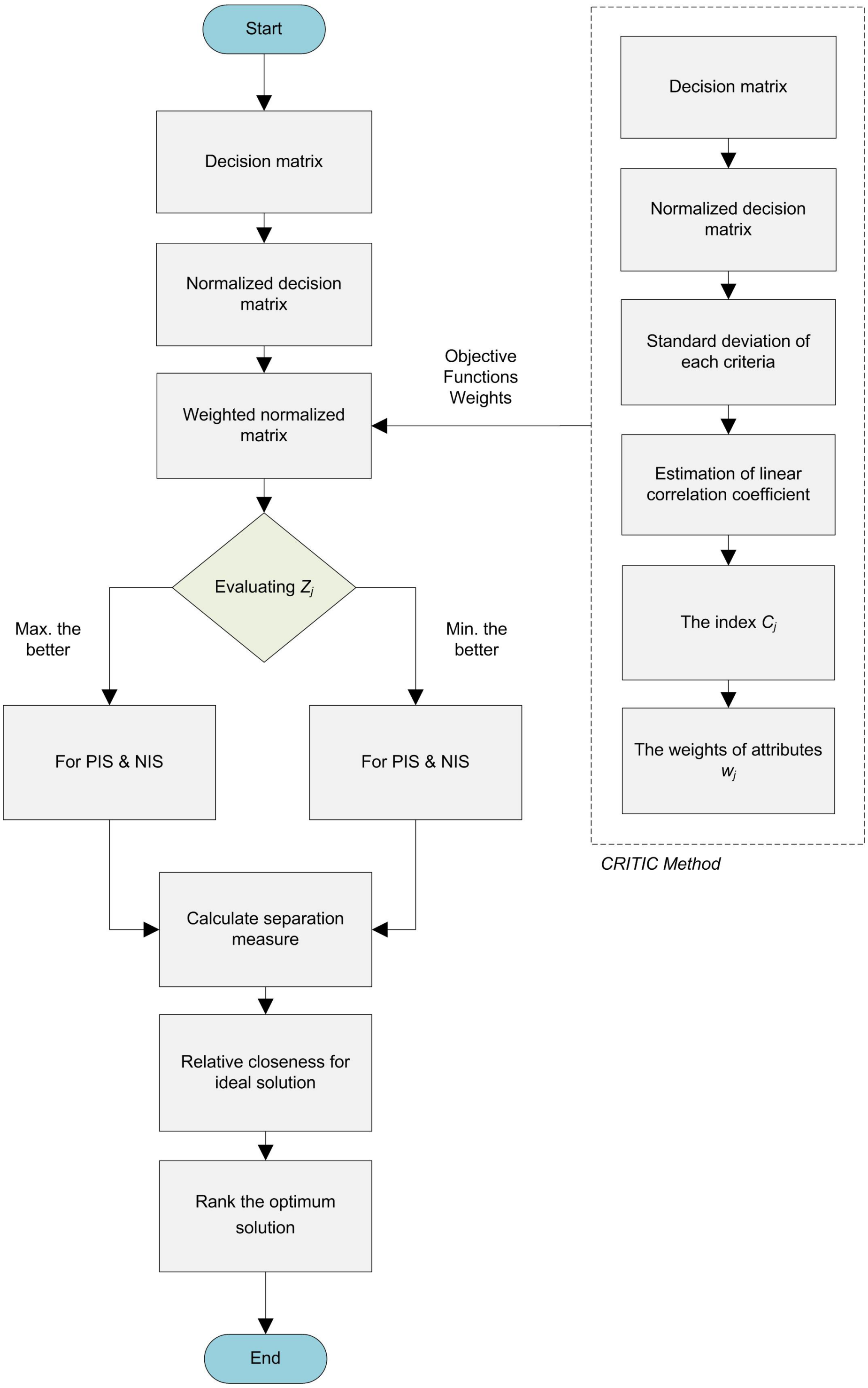


FIGURE 3.8: Flowchart of TOPSIS augmented with objective functions weights determined using CRITIC

Chapter 4

Sustainable and Resilient Supplier Selection and Order Allocation

In this chapter, the proposed methodology has been demonstrated by implementing phases 1-3 of the decision support framework that deal with SRSS-OA using data from the pharmaceutical industry. In the wake of COVID-19 pandemic, pharmaceutical industry has emerged as one of the most important and critical contributors to the global health care system.

Around the world, pharmaceutical firms have developed complex, international supply chain networks susceptible to disruptions. While SSS-OA ensures the well-being of the pharmaceutical industry under ordinary circumstances, incorporating resilience in this activity can help mitigate the adverse effects of disruptions, natural or otherwise, to the supply chain network.

All data concerning the number of suppliers, warehouses, transportation modes, capacity, and demand etc. was acquired from reputable firms engaged in manufacturing pharmaceutical items for decades. The relevant data has been included in Appendix C. The pharmaceutical supply chain considered comprises of 05 suppliers, 01 seaport, 01 dry port, 03 warehouses, and 02 customers.

4.1 Sustainability and Resilience Criteria Weighting

FE-AHP has been used for determining the weights of the sustainability and resilience criteria and sub-criteria based on the preferences of 04 DMs associated with the pharmaceutical industry. Value of the consistency ratio was calculated for all criteria collectively and for all sub-criteria entries within each criterion in order to ensure the soundness of the DMs' responses. The global and local weights of the criteria and sub-criteria along with the ranking of the sub-criteria have been included in Table 4.1.

TABLE 4.1: FE-AHP weights for sustainability and resilience criteria and sub-criteria

Criteria	**Global Weights**	**Sub-criteria**	**Local Weights**	**Ranking**
Economic	0.6	Product Price	0.02	5
		Payment Terms	0.02	5
		Product Quality	0.03	4
		Use of Technology	0.03	4
		Volume Flexibility	0.07	3
		Vendor's Reputation	0.07	3
		Responsiveness	0.12	2
		Product Mix	0.15	1
		Past Business	0.15	1
Environment	0.19	Environmental Management System	0.01	3
		Energy Consumption	0.02	2
		Waste Management System	0.02	2
		Innovative Capability	0.03	1
Social	0.14	Employee Health & Safety	0.01	3
		Staff Personal & Technical Development	0.02	2
		Information Disclosure	0.13	1
Resilience	0.06	Robustness	0.03	1
		Agility	0.02	2
		Leanness	0.02	2
		Flexibility	0.03	1

The sustainability and resilience criteria were presented as economic > environment > social along with resilience as an additional parameter for evaluation to

Table 4.2: Ranking of suppliers using FTOPSIS

Supplier	**EC**	**E_nC**	**SC**	**RC**	**Overall CC**	**Ranking**
Supplier-1	0.69	0.12	0.36	0.15	0.57	1
Supplier-2	0.68	0.16	0.14	0.15	0.559	2
Supplier-3	0.64	0.23	0.54	0.92	0.553	3
Supplier-4	0.5	0.3	0.68	0.61	0.407	4
Supplier-5	0.2	0.87	0.86	0.42	0.38	5

the DMs. Economic criteria was ranked as the most important one followed by environment, social, and then the resilience criteria. For the economic sub-criteria, past business and product mix have been identified as the most significant sub-criteria. Innovative capability has been ranked as the highest environment sub-criterion while information disclosure has been considered the most important social sub-criterion.

The DMs have ranked robustness and flexibility as the most important resilience sub-criteria. This discernable ranking of sub-criteria based on DMs' response serves as an aid for making informed decisions and to select only those suppliers that fulfill the sustainability and resilience criteria at the same time.

4.2 Sustainable and Resilient Supplier Ranking

FTOPSIS has been applied for ranking the potential suppliers using the weights of the sustainability and resilience criteria calculated in the preceding section and the response collected from the previously identified DMs. The closeness coefficient threshold for supplier ranking has been set at 0.5 and based on this value supplier-1, supplier-2, and supplier-3 have been selected for optimum order allocation while supplier-4 and supplier-5 have been retained as backup suppliers in case any of the selected suppliers becomes unavailable.

Using a modification of the procedure identified by Forghani et al. [130], a sensitivity analysis has been performed to evaluate the robustness of the selected suppliers. Based on the feedback received from the DMs, 08 sub-criteria have been short-listed for inclusion in the sensitivity analysis i.e. economic (product price, payment terms, responsiveness, and vendor's reputation), environment (environmental management system and innovative capability), social (information disclosure), and resilience (flexibility). A set of 06 different cases of varying degrees of sub-criteria weights has been considered and evaluated with reference to the current values of sub-criteria weights. In spite of the variations introduced in the sub-criteria weights, the ranking of the suppliers has remained unchanged. The outcome of the sensitivity analysis indicates that the MCDM methods applied have produced robust results for the sustainable and resilient supplier evaluation and selection problem. The final ranking of the potential suppliers has been included in Table 4.2. The details of the MCDM analysis have been presented in Appendix A.

TABLE 4.3: Optimum solutions of objective functions for time period t using nonlinear solver

Time Period	**Objective Function**	**Ideal Solution**
t_1	TC	$91136983.38
	TTT	621.6 h
	EI	750915.35 gm
	AQL	18680.02 kg
	TVSP	117241.22
t_2	TC	$93435628.21
	TTT	645.3 h
	EI	892574.29 gm
	AQL	18721.19 kg
	TVSP	116272.51
t_3	TC	$95265437.07
	TTT	634.2 h
	EI	957297.42 gm
	AQL	19938.52 kg
	TVSP	117252.96
t_4	TC	$96521876.81
	TTT	655.7 h
	EI	869374.61 gm
	AQL	19132.52 kg
	TVSP	119935.22

4.3 Sustainable and Resilient Order Allocation

The FMOMINLP mathematical model has been solved in two phases. First each objective function has been optimized individually using a nonlinear solver and ideal solutions have been determined as included in Table 4.3. In the second phase, AUGMECON2 has been employed for solving all objective functions simultaneously. Pareto solutions have been generated for each time period considered i.e. t_1-t_4 that correspond to quarters 1-4 of the calender year 2022, respectively, in order to determine the optimal order quantity for all selected suppliers using the fuzzified input data as included in Appendix C.

The accuracy and validity of the multi-objective optimization results is of vital importance as without reference to a benchmark value, any optimal solution will not be considered reliable. The results of the optimization of each objective function carried out separately using the nonlinear solver can help to address this issue. If the results of the multi-objective optimization have a close similarity to the results attained using the nonlinear solver, it can be established reliably that the solving algorithm has been able to handle the complexity of the multi-objective problem satisfactorily thus generating provable results.

In order to perform multi-objective optimization, AUGMECON2 first generates a payoff table for each time period t (Table 4.4). The maximum/minimum values of all objective functions are calculated by solving Eqs. 3.2-3.29 and the results have been presented in Tables 4.5 and 4.6, respectively. In the following step, the maximum and minimum values are divided into 10 segments and each segment is individually assigned to ε_2, ε_3, ε_4, and ε_5 with the step interval of 2 by using Eq. 3.33. These values have been included in Table 4.7.

The DMs have assigned 04 ϕ levels i.e. 0.25, 0.5, 0.75, and 1.0 for each solution with an incremental step of 0.25. The algorithm will run for every combination of ε values for all ϕ levels in order to generate Pareto optimal solutions. The maximum number of iterations allowed is 50,000. The last step in the sustainable and resilient order allocation process is the selection of the best solution from the set of Pareto optimal solutions generated by AUGMECON2.

Table 4.4: Payoff table using AUGMECON2 for time period t

Time Period	**Objective Function**	**TC ($)**	**TTT (h)**	**EI (gm)**	**AQL (kg)**	**TVSP**
t_1	TC	92804282.45	823.33	1755576.8	18475	105930.56
	TTT	93631359.24	608.86	849670.38	19475	119085.76
	EI	93631359.24	608.86	849670.38	19475	119085.76
	AQL	93631340.95	608.85	849652.81	19475	119085.76
	TVSP	95162050.42	611.33	850116.42	18975	119485.76
t_2	TC	91254980.23	797.25	1564291.6	18356	143597.22
	TTT	93473964.17	657.61	873693.43	18929	116293.91
	EI	93912579.05	629.43	865298.66	19574	116369.32
	AQL	93624579.66	602.43	869764.34	19578	116297.49
	TVSP	97253427.49	638.29	868265.55	19649	115679.64
t_3	TC	92673456.22	643.53	1427941.3	19246	152457.87
	TTT	95876521.09	687.47	942654.39	19925	117562.82
	EI	97648761.22	678.32	956482.21	19643	117465.97
	AQL	95790352.62	654.91	954278.23	19587	117790.11
	TVSP	96542752.79	667.01	957267.25	19647	117025.09
t_4	TC	97825790.25	686.38	1374825.2	19835	137923.34
	TTT	96257860.29	652.71	868734.56	19897	116432.66
	EI	96843789.34	652.82	873484.43	19642	119843.21
	AQL	96894392.55	655.72	862564.52	19528	119532.62
	TVSP	96654872.46	679.31	865782.37	19874	119376.01

TABLE 4.5: Maximum and Minimum Values of Objective Functions for t_1 and t_2

Objective Function	t_1		t_2	
	Max	**Min**	**Max**	**Min**
TC ($)	95162050.42	92804282.45	97253427.49	91254980.23
TTT (h)	823.33	608.85	797.25	602.43
EI (gm)	1755576.8	849652.81	1564291.6	865298.66
AQL (kg)	19475	18475	19649	18356
TVSP	119485.76	105930.56	143597.22	116293.91

TABLE 4.6: Maximum and Minimum Values of Objective Functions for t_3 and t_4

Objective Function	t_3		t_4	
	Max	**Min**	**Max**	**Min**
TC ($)	97648761.22	92673456.22	97825790.25	96257860.29
TTT (h)	687.47	643.53	686.38	652.71
EI (gm)	1427941.3	942654.39	1374825.2	862564.52
AQL (kg)	19647	19246	19897	19528
TVSP	152457.87	117025.09	137923.34	116432.66

This step is carried out by employing TOPSIS. The objective functions weights were calculated using CRITIC method and these values have been presented in Table 4.8. Only one solution can be selected by the DMs for each time period. The values of the relative closeness coefficient for the best 20 Pareto optimal solutions for the time periods t_1-t_4 have been included in Table 4.9. The best solution for each time period has been presented in Table 4.10.

Table 4.7: ε-Values of TTT, EI, AQL, and TVSP

Time Period		**ε-values**			
		ε_1	ε_2	ε_3	ε_4
1	t_1	608.85	849852.81	18475	105930.56
	t_2	716.09	849652.71	18425	109831.37
	t_3	823.33	849652.21	18375	110718.26
	t_4	608.85	1302614.8	18475	115701.11
2	t_1	608.85	1302614.8	18375	105930.16
	t_2	716.09	849652.81	19575	108921.84
	t_3	823.33	849652.81	17965	112222.01
	t_4	608.85	849752.81	17985	117728.19
3	t_1	608.85	1302614.8	18355	105930.06
	t_2	716.09	859252.81	18925	111392.11
	t_3	823.33	889652.61	18765	112421.17
	t_4	608.85	819652.01	19971	116133.15
4	t_1	608.85	859652.81	19975	105930.06
	t_2	823.33	846652.91	19673	111929.72
	t_3	608.85	849752.81	18455	114441.06
	t_4	823.33	1302614.8	19415	115792.19
5	t_1	823.33	1302614.8	19815	105930.72
	t_2	608.85	849652.33	18415	109431.82
	t_3	823.33	847652.61	19121	112416.15
	t_4	608.85	845652.09	18415	115719.82
6	t_1	608.85	849652.81	19415	105930.28
	t_2	608.85	849752.91	19411	106931.65
	t_3	716.09	848652.29	18471	114563.12
	t_4	823.33	849752.81	19471	115708.11
7	t_1	608.85	889652.86	19915	105930.52
	t_2	716.09	848652.81	19915	105930.86
	t_3	823.33	889652.88	19915	112518.15
	t_4	608.85	1302614.8	19915	114401.26
8	t_1	823.33	1755576.8	18915	105930.26
	t_2	608.85	849652.86	19975	107531.52
	t_3	823.33	848652.81	19915	114478.12
	t_4	608.85	889652.97	19414	117719.11
9	t_1	823.33	849672.81	18425	105930.23
	t_2	608.85	848652.91	18415	104948.35
	t_3	823.33	859652.88	19371	114545.11
	t_4	608.85	1755576.8	19275	118715.16
10	t_1	823.33	1755576.8	18415	105930.15
	t_2	608.85	849652.86	18585	110943.54
	t_3	823.33	848652.81	19471	111927.14
	t_4	608.85	839672.69	19475	117934.29

TABLE 4.8: CRITIC Weights for Objective Functions for t_1-t_4

Objective Function	**Weight**			
	t_1	t_2	t_3	t_4
TC	0.21	0.21	0.2	0.25
TTT	0.1	0.1	0.15	0.15
EI	0.1	0.1	0.17	0.12
AQL	0.25	0.22	0.2	0.18
TVSP	0.34	0.37	0.28	0.3

TABLE 4.9: Relative Closeness Coefficient (CC) Matrix for Pareto solutions of AUGMECON2 for t_1-t_4

		Time Period			
		t_1	t_2	t_3	t_4
CC	1	0.944	0.742	0.961	0.958
	2	0.885	0.692	0.838	0.974
	3	0.851	0.852	0.659	0.862
	4	0.788	0.952	0.271	0.681

The details of the MCDM analysis performed for identifying the best solution have been included in Appendix D. This analysis is based on applying fuzzy E-AHP for determining global and local weights of all sustainability and resilience criteria and sub-criteria. These weights are used in fuzzy TOPSIS to rank all suppliers.

Once an initial ranking of suppliers has been determined, a sensitivity analysis is applied to evaluate the selected suppliers to see how they will react to any random changes in the values of DM identified sub-criteria.

TABLE 4.10: Best optimal solution of each objective function for t_1-t_4

	CC	**TC ($)**	**TTT (h)**	**EI (gm)**	**AQL (kg)**	**TVSP**
t_1	0.944	93224195.91	736.22	849670.38	18564	108357.88
t_2	0.952	94678327.81	699.13	887235.25	19741	112319.02
t_3	0.961	92675287.52	647.02	957162.45	19623	115791.21
t_4	0.974	96589852.26	691.72	878519.31	19738	117301.06

4.4 Discussion

The literature analysis presented in Chapter 2 has revealed that SRSS-OA problem has been studied extensively over the years but with certain limitations. For example, Sen et al. [104] and Mahmoudi et al. [109] have considered environmental and resilience criteria for the purpose of supplier selection but the remaining TBL sustainability criteria and the order allocation part of the SRSS-OA problem has been ignored in their modeling approach. Amindoust [105], Jabbarzadeh et al. [106], and Fallahpour et al. [107] have employed TBL sustainability and resilience criteria for supplier selection but order allocation has not been taken into account in any of these research studies.

Hosseini et al. [12] have presented a mathematical model for order allocation based only on economic and resilience criteria and the supplier selection part has not been considered while implementing this research work. A propensity for partial inclusion of assessment criteria and concentration on any one component of the sustainable and resilient SS-OA problem is a major shortcoming of extant literature. To address this shortcoming, the proposed integrated methodology has been implemented through a holistic decision support framework employing relevant, systematically chosen TBL sustainability and resilience criteria. The utility and potential of the decision support framework has been demonstrated using data from the pharmaceutical industry, which has not been carried out earlier in any of the research works highlighted above.

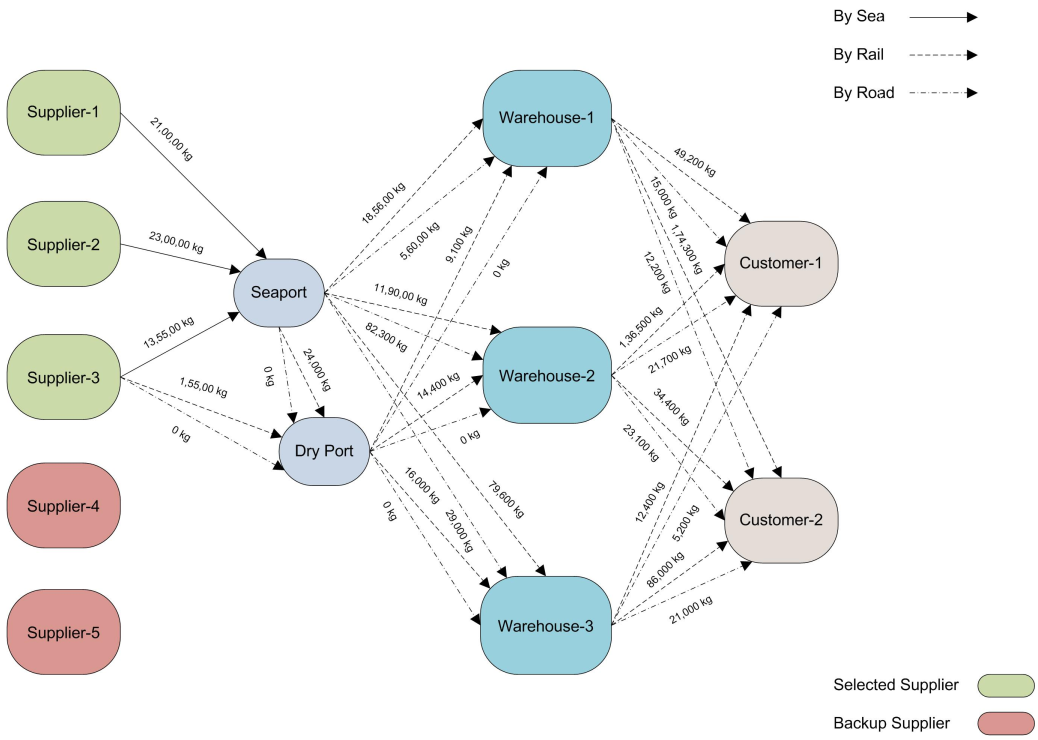
It has been observed that the Pareto optimal solutions generated through multi-objective optimization have close similarity to the ideal solutions calculated using the nonlinear solver, as included in Section 4.3. Multi-objective optimization is computationally more challenging as compared to solving each objective function individually.

However, it has been observed that AUGMECON2 as a solving algorithm can handle the complexity of the extensive supply chain network presented in Fig. 3.1 without recourse to specialized computational resources. The combination of sustainability and resilience criteria for supplier selection and the inclusion of resilience criteria weights in the FMOMINLP mathematical model has enabled a more holistic evaluation of the SRSS-OA problem in the context of the pharmaceutical industry. A graphical representation of the order quantities allocated to the selected suppliers has been presented in Figs. 4.1 and 4.2 for all time periods considered.

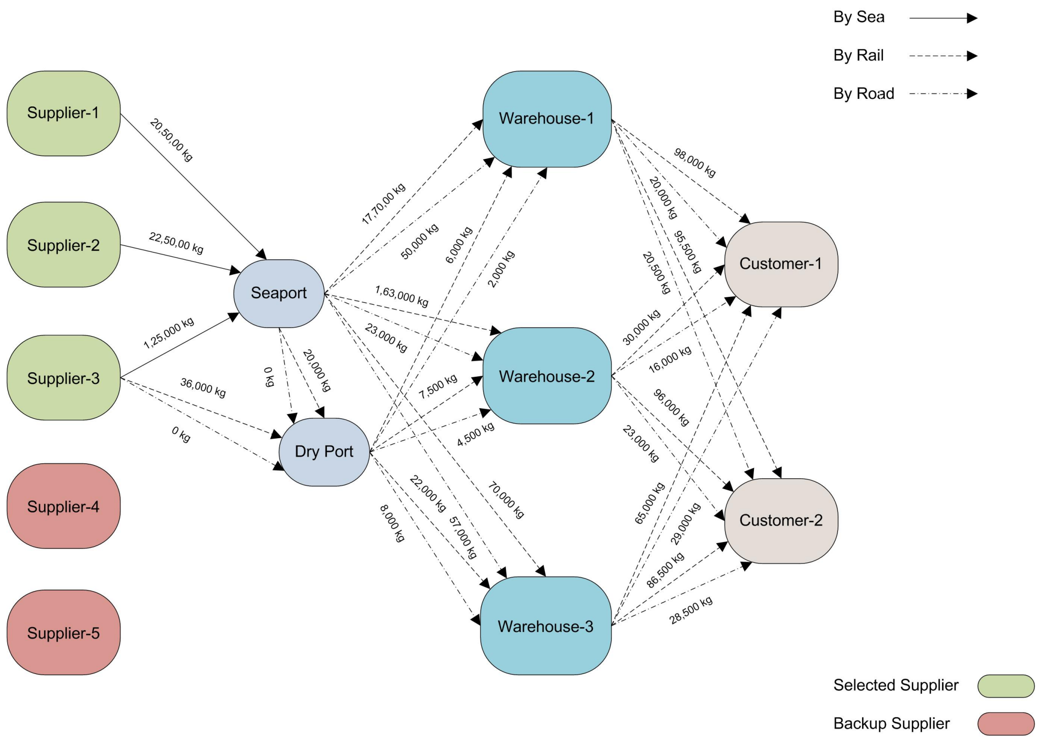
In order to assess the effectiveness of the proposed methodology in handling the impact of natural or manmade disruption scenarios on the performance of the pharmaceutical supply chain network, multiple random and intentional disruptions have been introduced and evaluated based on the procedure outlined in phase 4 and phase 5 of the decision support framework.

The details of the implementation and results of the analysis have been presented in the following chapter. It is pertinent to note that the contents of Chapter 4 and Chapter 5 together present the complete demonstration of the multi-phase decision support framework. Any meaningful inference about the performance of the decision framework can only be made if the implementation and results of the application case study are analyzed in their entirety.

This brief discussion serves as a link to connect the implementation and results of the first 3 phases of the decision support framework (dealing with SRSS-OA) to those of the last 2 phases of the decision framework (dealing with disruption scenario evaluation) presented in Chapter 5. The theoretical and managerial significance of the results of the complete implementation of the decision support framework has been included in Chapter 6.

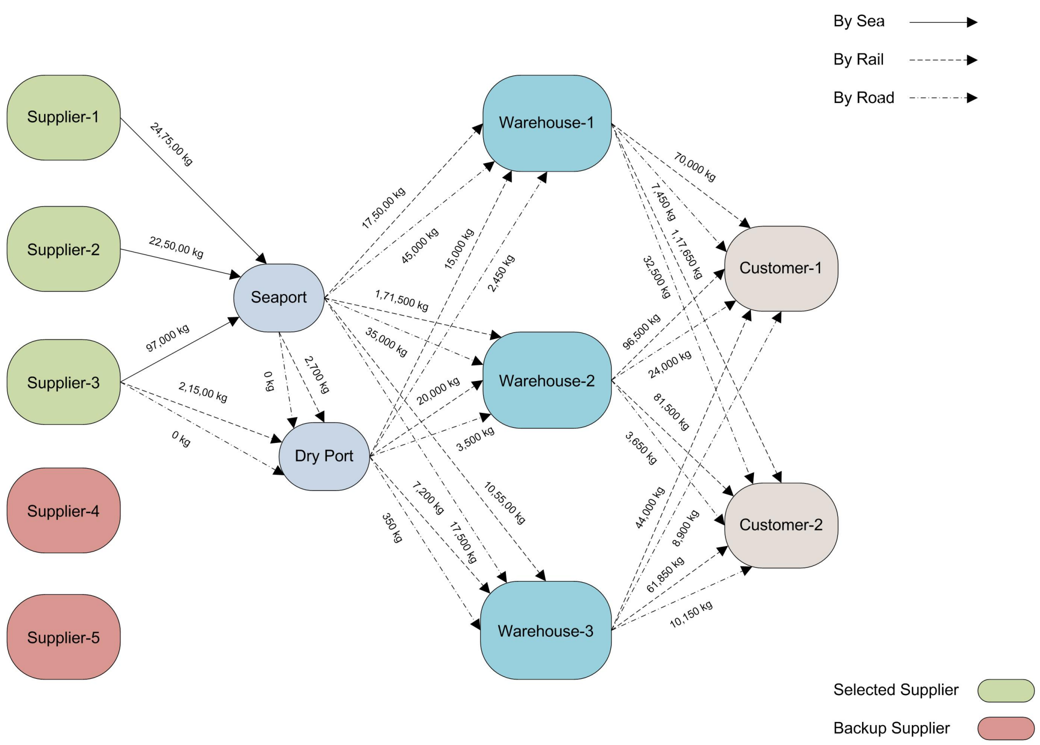


(a) Time period t_1

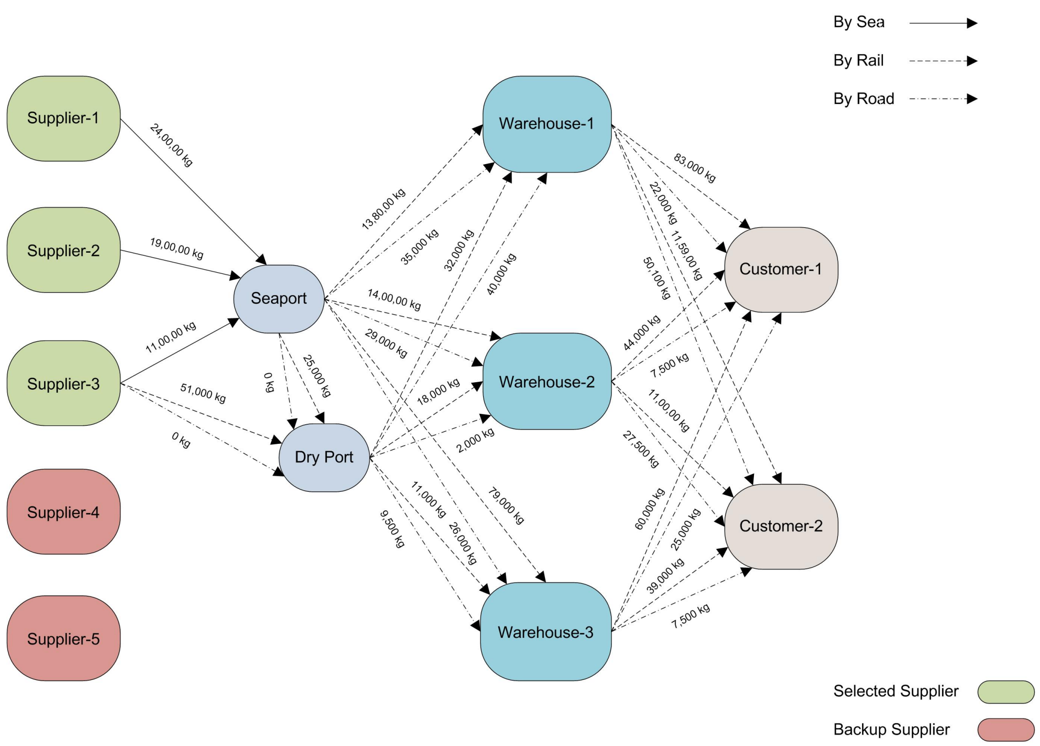


(b) Time period t_2

FIGURE 4.1: Breakdown of Order Allocation Quantities for t_1 and t_2



(c) Time period t_3



(d) Time period t_4

FIGURE 4.2: Breakdown of Order Allocation Quantities for t_3 and t_4

Chapter 5

Evaluation of Demand Uncertainty and Network Disruptions

For the integrated SRSS-OA methodology developed in the present research work, the effectiveness of the multi-phase, multi-period decision support framework has been evaluated by considering the attainment of a predetermined service level by the supply chain as a performance target under the influence of random (probabilistic) and intentional (network) disruptions. The order allocation solutions generated using the FMOMINLP mathematical model have been compared for both ideal, no disruption and disruption situations in order to identify the best performance configuration for the multi-modal, multi-echelon supply chain network considered in the application case study problem.

5.1 Random (Probabilistic) Disruptions

If the demand rate is constant and deterministic throughout the year, all inventory replenishment decisions can be made using the economic order quantity (EOQ) model. On the other hand, if the demand is variable or probabilistic, then it can only be described by a probability distribution and the EOQ model is no longer applicable. With probabilistic demand, inventory decisions become more complicated as the time the reorder point will be reached, the time between reorders, or the time the order will arrive in the inventory cannot be determined in advance. This lead time uncertainty may cause occasional shortages or stock-outs and the supply chain network service level may be affected.

A number of probability distributions have been used for inventory decisions with regard to demand uncertainty in extant literature, the most basic and widely used being the normal distribution. When lead time disruptions are taken into account for evaluating the impact of demand uncertainty on supply chain network service level, a continuous probability distribution i.e. normal or a discrete probability distribution i.e. Poisson or binomial may be used [11, 111, 143].

In supply chain networks, inventory control defines how often inventory levels are reviewed in order to determine when and how much to order. This is usually carried out either by implementing a continuous review or a periodic review inventory system. In a continuous review inventory system, the state of the inventory is monitored continuously so that an order can be placed whenever the reorder point is reached whereas in a periodic review inventory system, the inventory is checked and reordering is only carried out at fixed intervals of time. Both inventory systems have their benefits and limitations and the choice is usually made depending upon the design and operation of the supply chain network being evaluated.

The demand forecast data of last 05 years for the pharmaceutical supply chain network presented in this research work shows considerable variation (Appendix E). The demand uncertainty has an impact on the service level of the supply chain network and the DMs are always concerned that in the face of demand fluctuations, a stock-out might occur. In order to mitigate this situation, a 01% chance of stock-out is introduced, which reduces the service level of the supply chain network to 99%.

This possibility of a stock-out happening is a random and a lead time disruption and to ensure that the service level is maintained by the supply chain for the review period considered i.e. 03 months or 01 quarter, a safety stock is required over and above the forecast demand quantity.

The two customers serviced by the supply chain network are in fact two different manufacturing units owned and operated by one pharmaceutical firm. Both manufacturing units are autonomous and produce medicament items like veterinary medicine and health supplements. The raw materials consumed by both manufacturing units are similar therefore their separate demand order quantities have been consolidated for evaluation purposes in the following analysis.

The particular type of product (or the raw material for the two customers) that has been considered while implementing the application case study problem is acquired from overseas suppliers and involves extended durations of transportation time. The two customers have adopted a periodic review system for inventory control partly due to the multi-product nature of their manufacturing operation and in response to the logistics of the import and procurement operation as well.

The lead time although considerable is assumed shorter than the length of the review period and any order placed at a review period will be received prior to the next review period. For the periodic review inventory system, the how much to order decision for any review period is given by Eq. 5.1 where, Q is the order quantity, M is the replenishment level, and H is the inventory on hand at the review period.

$$Q = M - H \tag{5.1}$$

The order quantity at each review period must be sufficient to cover demand for the review period plus the demand for the following lead time. That is, the order quantity that brings the inventory position up to the replenishment level M should last until the order made at the next review period is received in the inventory. In this case the total duration considered will be equal to the review period plus the lead time. The normal probability distribution of demand during the review period and the lead time for the application case study problem has been included in Fig. 5.1.

The mean value μ of the demand is 3,65,866 kg with a standard deviation σ of 1,46,720 kg. Using the normal probability distribution, the relation for M is given

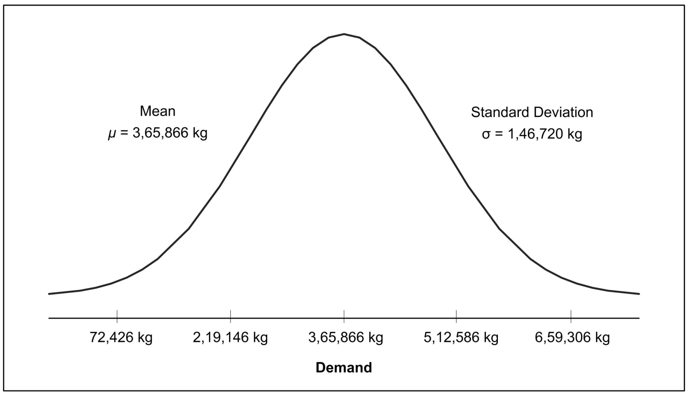


FIGURE 5.1: Probability distribution of demand during the review period and lead time

by Eq. 5.2 where, z is the number of standard deviations required to achieve the acceptable stock-out probability.

$$M = \mu + z\sigma \tag{5.2}$$

Using Eq. 5.2 and substituting the values of μ and σ from Fig. 5.1 and the value of z from the normal probability distribution table for 01% probability of stock-out, the value of replenishment level M is calculated as 7,07,725 kg (Fig. 5.2).

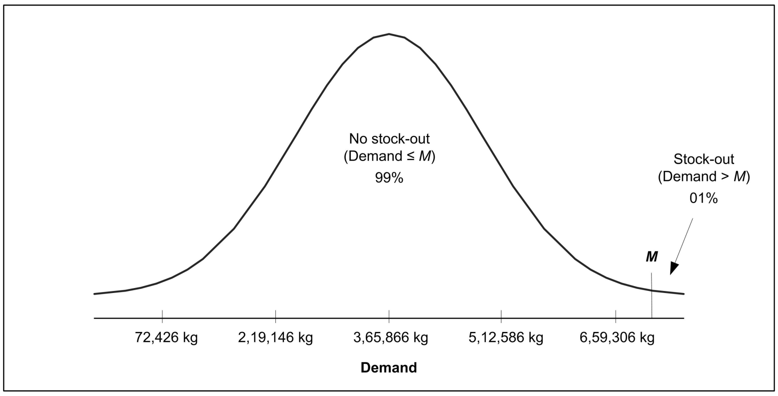


FIGURE 5.2: Replenishment level M that allows a 01% stock-out probability or 99% service level

The value of the safety stock required to ensure a 99% service level for the supply chain network can be calculated by using Eq. 5.1 by substituting the values of the forecast inventory at the start of the review period and of the replenishment level determined above. For the application case study presented here and the review period considered, this value comes out to be 1,17,742 kg.

The value of replenishment level M has been used to determine revised demand values for both customers and the FMOMINLP mathematical model has been re-implemented using quarter-1 (Q1)[1] data (Appendix E) in order to generate Pareto optimal values of all objective functions with 01% stock-out probability or 99% service level. The results have been included in Table 5.1.

Table 5.1: Optimal results for lead time disruption (Q1 data)

TC ($)	**TTT (h)**	**EI (gm)**	**AQL (kg)**	**TVSP**
109565460.290	1041.448	2480202.685	22198.113	134590.410

5.2 Intentional (Network) Disruptions

A supply chain network is composed of different organizational entities that are connected by the physical flow of materials. These entities located along the network are referred to as nodes and they may be involved with the conversion, logistics, or the selling of materials. The inter-node relationships or the movement of materials among these entities is identified by using unidirectional or bidirectional arrows that may be termed as arcs or edges of the supply chain network. A complete representation of a supply chain would usually involve locating all nodes and all edges between a specific point of origin and a specific point of final consumption. This set of nodes and the associated pattern of edges among these nodes may be referred to as the supply chain network design. The performance of a supply chain is ultimately linked with the interconnectivity of its constituting elements i.e. nodes and edges. An evaluation of this interconnectivity may help to identify those nodes and edges that are critical for the proper functioning of the network.

A multi-method, multi-source empirical research study has been employed by Craighead et al. [144] for identifying three design characteristics that greatly influence supply chain network performance in the face of disruptions i.e. supply

[1] Q1 refers to quarter-1 of the calender year 2022.

chain density, supply chain complexity, and node criticality. Supply chain density signifies the geographical spacing of nodes within a supply chain network i.e. in a dense supply chain, the nodes are located closer together and vice versa. Supply chain complexity is defined as the sum of the total number of nodes and the total number of forward, backward, and within-tier material flows within a supply chain network being evaluated. Node criticality refers to the relative importance of a node within a supply chain and can be used either to characterize a specific node within a supply chain network or a property of the entire supply chain.

All nodes within a supply chain network, in theory, should play a value addition role, and all nodes are considered important and significant to the smooth operation of the supply chain. But in practice, some nodes within the supply chain network may be deemed more important than the others due to their location or due to the contribution they make to the value addition process i.e. a critical supplier, a vital point of entry to a geographical location, or an indispensible distribution center etc.

The degree of connectivity and throughput rate of a node may be used as two characteristics that signify the relative importance of a node within a supply chain network. A simple quantitative metric that combines these two attributes in order to identify critical nodes has been proposed by Plaganyi et al. [142]. For a supply chain node j being evaluated, this quantitative metric termed Supply Chain Index (SCI) can be calculated using Eq. 5.3.

$$SCI_j = \sum_{i=1}^{n} s_{ji} p_j^2 \tag{5.3}$$

For a supply chain model comprising of n nodes, s_{ji} represents the proportion of the total product that a receiver node j receives from a supplier node i relative to all product flowing into the receiver node j, such that for node j, the following condition as given by Eq. 5.4 is satisfied.

$$\sum_{i} s_i = 1 \tag{5.4}$$

In Eq. 5.3, the variable p_j measures the proportion of the total product in the supply chain network that flows into the receiver node j, so that the product of the two variables s and j represents both connectance and magnitude of flow. The node(s) with the highest SCI score(s) will be identified as the critical node(s). The SCI can be applied by using either the volume of the product handled by the supply chain or the value added at different stages as the product flows along the network depending upon the type of the system being considered or suitable data being available. The ability of SCI to handle supply chain complexity and node criticality together, and to evaluate all network components based on this unified criterion with due concern for supply chain response to potential disruptions makes it highly useful, in comparison with other methods presented in extant literature.

The pharmaceutical supply chain network presented in this research work has been evaluated using SCI in order to identify critical nodes based on the order quantity data of the two customers. The results for the Q1 data have been included in Table 5.2 where port-1 refers to the seaport and port-2 refers to the dry port. The terminal elements of the supply chain network i.e. suppliers and customers have been excluded from this analysis. The details of the critical node and link analysis have been presented in Appendix F.

TABLE 5.2: SCI scores for pharmaceutical supply chain network (Q1 data)

Node	Port-1	Port-2	Warehouse-1	Warehouse-2	Warehouse-3
SCI	0.11857	0.00129	0.16127	0.10864	0.02962

From the data presented in Table 5.2 and graphically compared in Fig. 5.3, the seaport and warehouse-1 have been identified as the critical nodes as they carry the maximum values of SCI score in their respective categories. The seaport is indispensible to the operation of the supply chain network considered in the application case study as it serves as a key entry point for goods acquired from overseas suppliers. In this instance, the volume of goods transported through the seaport is such that if it is knocked out, the entire supply chain will collapse. As the intentional knocking out of different components of the supply chain network

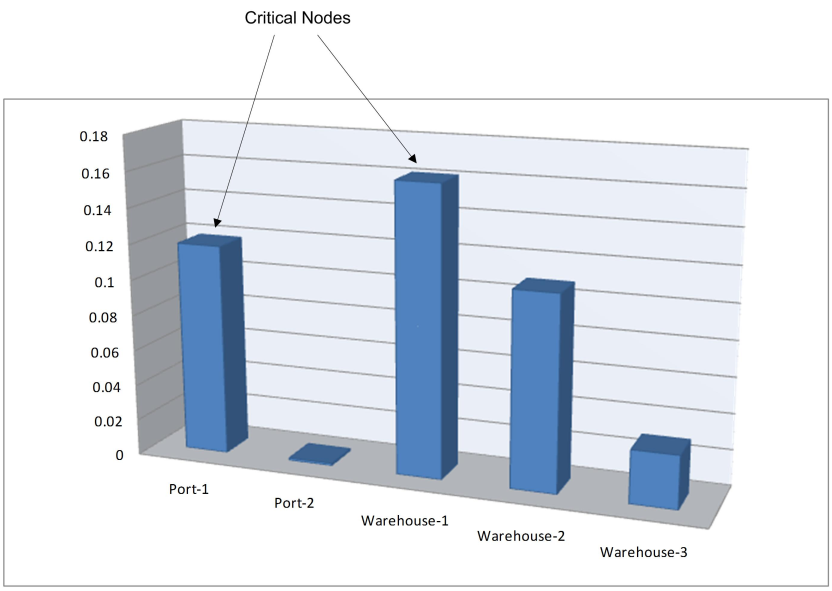


FIGURE 5.3: A comparison of SCI scores of pharmaceutical supply chain network nodes

is based on a random choice, any node can be chosen for demonstrating the impact of the intended disruption. The SCI score of the dry port is only a fraction of the value determined for the seaport yet the dry port may have an important role to play as it facilitates overland shipments by a supplier located in a geographically contiguous country.

In order to analyze the performance of the pharmaceutical supply chain network in maintaining a predetermined value of the service level i.e. 99% (same as that considered for the lead time disruption for comparison purposes) in the face of disrupting events that knockout one or more of the supply chain components, certain nodes have been intentionally removed from the network, and the FMOMINLP mathematical model has been re-implemented using Q1 data with revised demand values.

Three disruption scenarios have been considered and evaluated one by one while keeping the rest of the problem settings constant: (a) supplier-2 not available, (b) port-2 not functional, and (c) warehouse-2 out of service. For mitigating the adverse effects caused by the unavailability of supplier-2, supplier-4 has been incorporated as a substitute supplier. The results for the three network disruption scenarios considered have been included in Tables 5.3-5.5.

Table 5.3: Optimal Results for Supplier-2 Not Available (Q1 data)

TC ($)	TTT (h)	EI (gm)	AQL (kg)	TVSP
111133593.220	1047.350	2510740.612	27488.138	125006.218

Table 5.4: Optimal Results for Port-2 Not Functional (Q1 data)

TC ($)	TTT (h)	EI (gm)	AQL (kg)	TVSP
109606018.440	872.508	1713678.691	25137.492	132992.103

Table 5.5: Optimal Results for Warehouse-2 out of Service (Q1 data)

TC ($)	TTT (h)	EI (gm)	AQL (kg)	TVSP
109494201.010	809.444	1070580.615	22524.350	135190.722

5.3 Comparison of No Disruption and Disruption Scenarios

A brief evaluation and comparison of the no disruption solution to the results of the supply chain network being assessed under the influence of 01 probabilistic and 03 network disruptions as described in the previous sections has been presented below.

A substantial increase in the value of the total cost has been observed between the no disruption solution and the results for all 04 disruption scenarios considered (Fig. 5.4, Part (a)). For the target service level i.e. 99% maintained by the supply chain network, only a minor variation exists between the optimal values of the total cost determined for all disruption scenarios when evaluated using the FMOMINLP mathematical model.

An increasing trend has been observed in the values of the total travel time between the no disruption solution and disruptions caused by the lead time variation

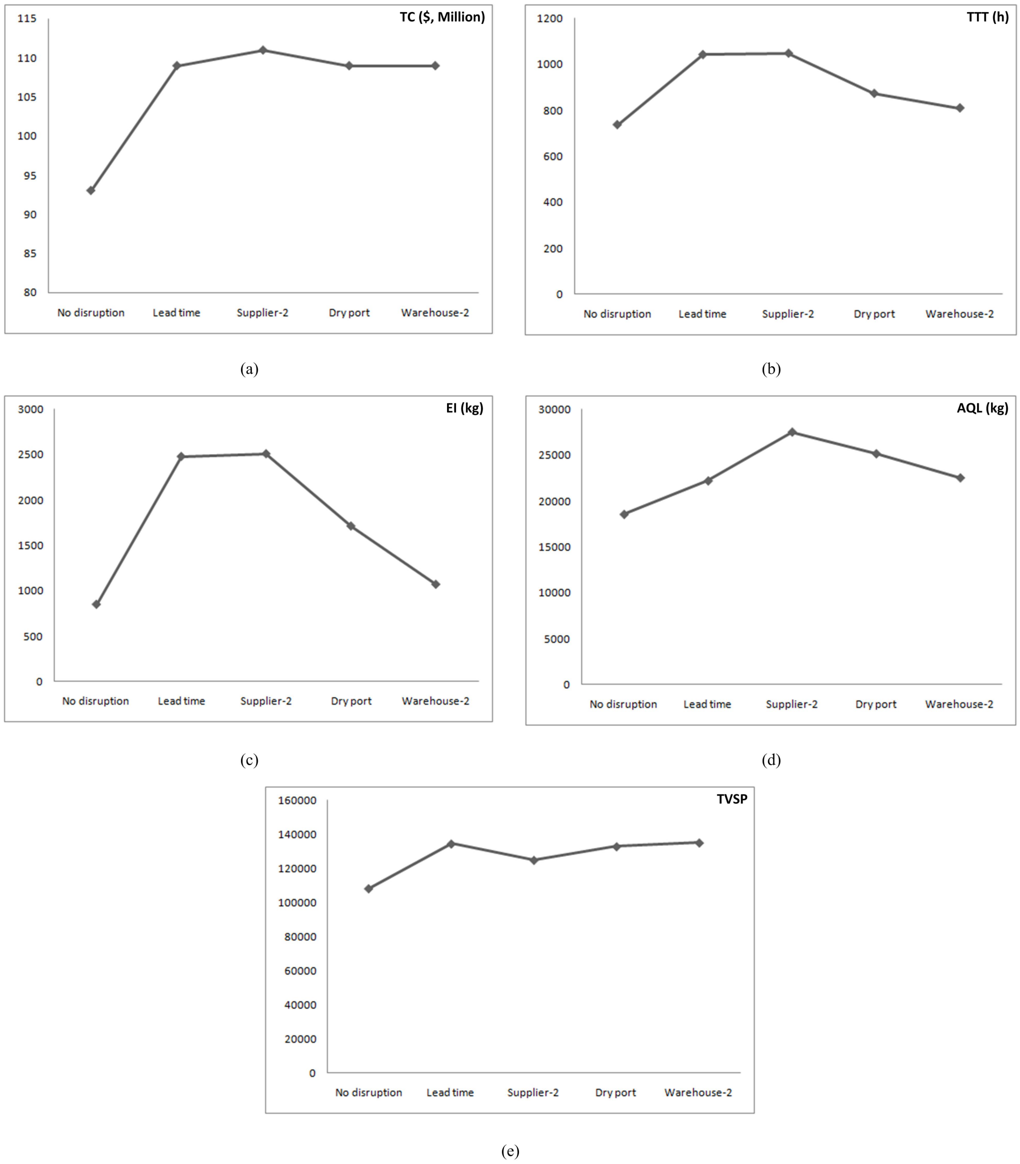


FIGURE 5.4: Comparison of No Disruption and Disruption Solutions

and unavailability of supplier-2 (Fig. 5.4, Part (b)). In case of the disruption scenarios created due to the dry port and warehouse-2 being knocked out, the total travel time is reduced as the goods are transported through alternate routes. This reduction in the total travel time has its downside as well as the value of the total cost increases and the storage capacity of the remaining two warehouses may be constrained to the limit.

The variation in the values of the total travel time is closely linked with the environmental performance of the supply chain network (Fig. 5.4, Part (c)). A sharp increase has been observed in the values of the environmental impact for the lead time disruption and the substitution of the backup supplier. As total travel time is reduced due to removal of the dry port and the warehouse-2 from the supply chain network, the environmental impact is correspondingly reduced. An increase or decrease in the value of the environmental impact is only linked with the total cost through a relative variation in the value of the total travel time.

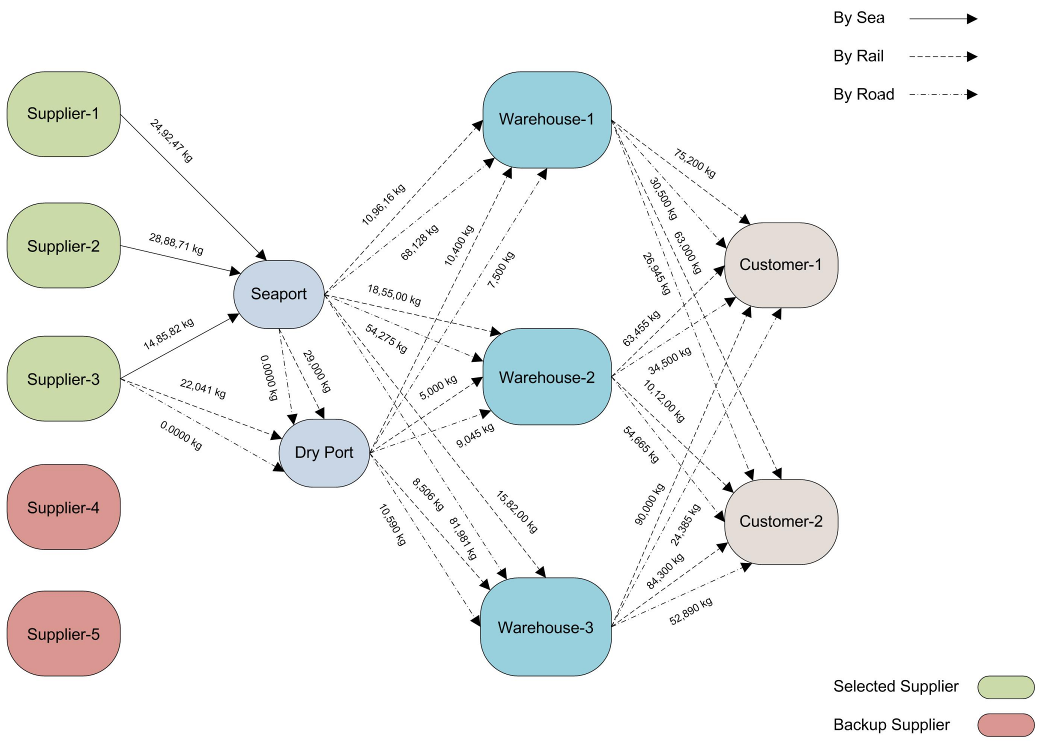
A noticeable difference in the values of the acceptable quality limit has been observed for the no disruption and disruption solutions presented in Fig. 5.4, Part (d). The maximum increase in the value of the acceptable quality limit is associated with the substitution of the backup supplier for replacing supplier-2.

An increase has been observed in the total values of sustainable purchasing for all disruption scenarios considered (Fig. 5.4, Part (e)). This increase is attributable to the service level requirement imposed on the supply chain network. The reduced risk performance of the backup supplier (ranked 4 out of the total 5 suppliers considered) is reflected by its total value of sustainable purchasing, which is the lowest among all disruption scenarios presented in Fig. 5.4, Part (e).

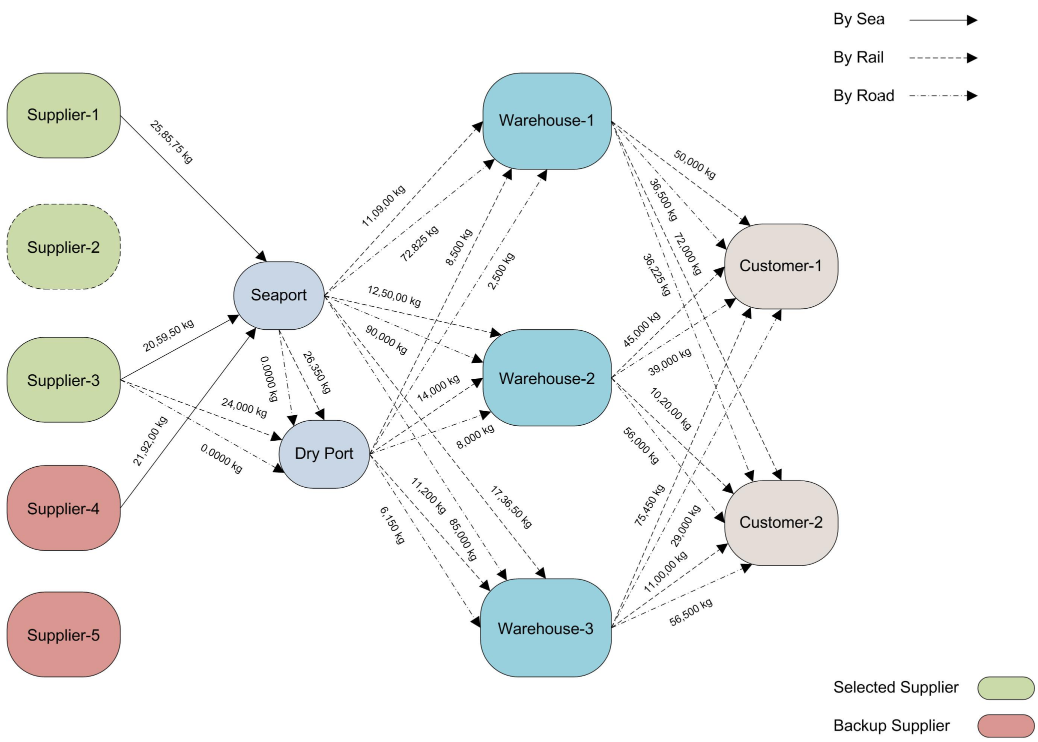
In summary, any strategy adopted for countering the impact of disruptions will generally lead to an increase in the cost, transportation time, or environmental impact of the supply chain network operations, or it may cause inadvertent lapses in quality control and reliability procedures while accommodating new suppliers and/or logistic or distribution partners etc.

It is the delicate task of the DMs to take a holistic view of the situation while evaluating a potential disruption scenario and suggest suitable countermeasures. The SRSS-OA methodology presented in this research work coupled with the strategy for evaluating the impact of supply chain disruptions can be applied as a useful aid for this purpose.

A graphical representation of the breakdown of the optimal order allocation quantities for all 04 disruption scenarios considered above determined using Q1 data has been included in Figs. 5.5 and 5.6, respectively. The extent of the variation of optimal order quantities that exists among different nodes of the supply chain network for no disruption and disruption solutions can be noticed by a visual comparison of the aforementioned figures with Fig. 4.1, Part (a).

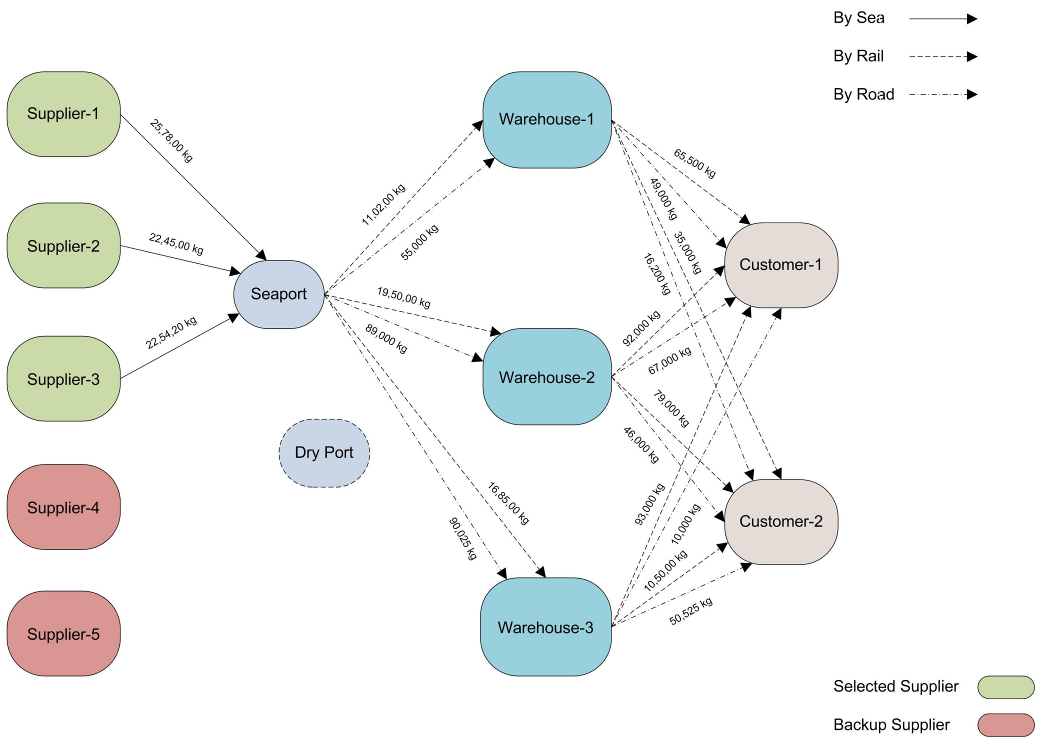


(a) Scenario-1: Lead time disruption (01% stock-out risk, 99% service level)

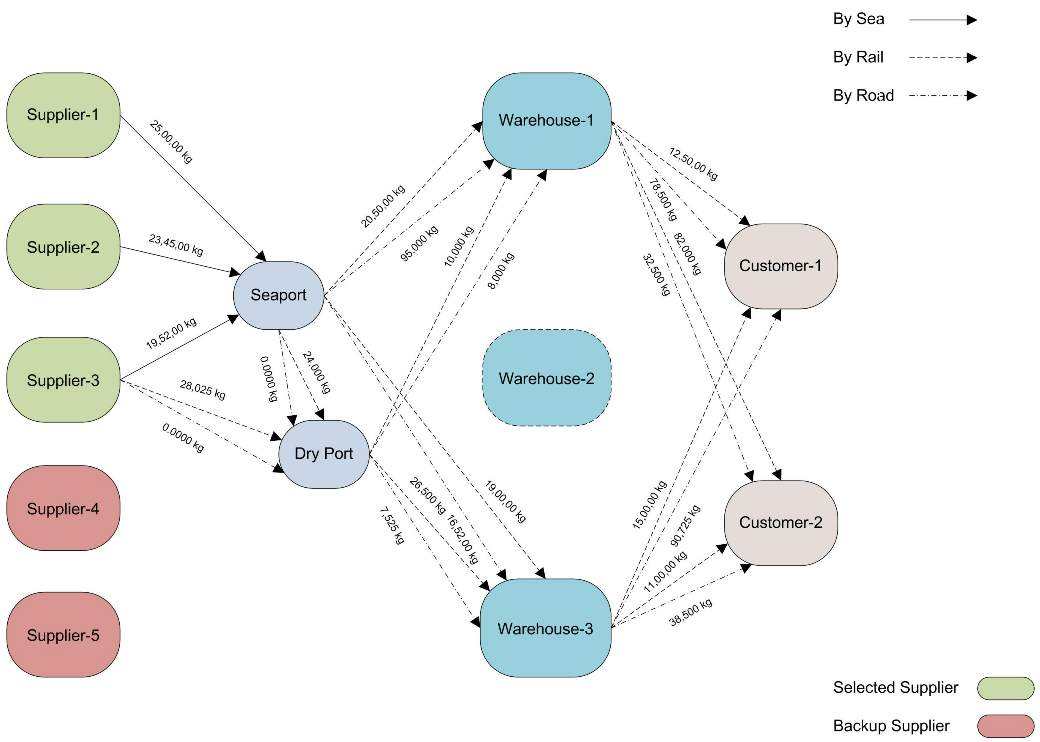


(b) Scenario-2: Supplier-2 not available (99% service level)

FIGURE 5.5: Breakdown of Order Allocation Quantities for t_1 Under Disruption Scenarios 1 and 2



(c) Scenario-3: Dry port not functional (99% service level)



(d) Scenario-4: Warehouse-2 out of service (99% service level)

FIGURE 5.6: Breakdown of Order Allocation Quantities for t_1 Under Disruption Scenarios 3 and 4

Chapter 6

Conclusion and Future Work

6.1 Conclusions

In this research thesis, a novel comprehensive multi-phase, multi-period decision support framework has been proposed for sustainable and resilient SS-OA subject to disruption risks. The proposed framework has been demonstrated using real-time data collected from the pharmaceutical industry. The decision support framework has been implemented in 2 parts i.e. in the first part comprising of phases 1-3, sustainable and resilient SS-OA has been carried out, which is followed by disruption scenario evaluation and comparison of no disruption and disruption solutions in the second part consisting of phase 4 and phase 5, respectively. The following conclusions may be drawn from the results gained by implementing phases 1-3 of the decision support framework:

(a) The TBL sustainability sub-criteria product price, past business, innovative capability, and information disclosure have been ranked as the most important attributes for supplier evaluation and selection by the DMs in the pharmaceutical industry.

(b) The resilience sub-criteria robustness and flexibility are considered the most valued characteristics in the potential suppliers as reported by the DMs.

(c) The transfer cost and custom clearance cost comprise 69.4% of the total cost of the supply chain network. On the other hand, transfer time and custom clearance time comprise only 24.7% of the total transportation time.

(d) Transportation by sea has the least impact on environment (8.2%) while transportation by rail has the highest rate of environmental impact (62.5%) followed by transportation by road (29.5%).

(e) Transfer of goods by rail is the most preferred mode for inland transportation. This mode of transportation is also favored by potential suppliers located in geographically contiguous countries.

The uncertainty encountered in actual supply chain network operations has been incorporated both in the supplier selection and the order allocation parts of the proposed framework using FST. The input data collected from the industry has also been fuzzified in order to make the modeling more realistic and closer to real-time situations. The SRSS-OA problem has been previously addressed by many researchers in extant literature but with certain critical limitations i.e. the tendency towards selective evaluation of TBL sustainability and resilience criteria, omitting risk/resilience criteria from order allocation, or excluding either supplier selection or order allocation from the analysis all together etc.

A significant contribution of the research work presented in this thesis is that it addresses all these shortcomings and leads to a holistic and inclusive integrated methodology for supplier evaluation and selection, and optimal order quantity allocation based on all TBL sustainability criteria coupled with resilience in all parts of the SRSS-OA problem. The effectiveness of this integrated methodology has been evaluated by considering and incorporating the effects of contingency or disruption scenarios on the performance of the supply chain network by using a simplified yet effective procedure as outlined in phase 4 and phase 5 of the decision support framework. Based on this evaluation, following conclusions are pertinent:

(f) It has been observed that all disruption scenarios being evaluated lead to a significant increase in the total cost when compared with the no disruption solution due to the enhanced order quantities required for achieving and maintaining the target supply chain network service level. A maximum increase of 19.2% has been observed for the disruption scenario when supplier-2 becomes unavailable.

(g) Lead time variation and the unavailability of a supplier causes an increase in the total travel time while the disabling of nodes and links within the supply chain network leads to a reduction in the total travel time as the order quantity is transported through alternate routes with shorter distances. This may also cause the volume of the order quantity being transported along a particular route to increase and lead to constraining the capacity of the transportation mode or the warehouse handling the shipment. A maximum increase of 42.3% has been noticed in the value of TTT when the backup supplier is substituted to replace supplier-2 with lead time disruption a close second at 41.5%.

(h) Any variation in the logistics performance of the supply chain network is directly linked with a change in the value of the environmental impact. Lead time disruption and the replacement of supplier-2 with the backup supplier bring about almost a threefold increase in the value of EI when compared with the no disruption solution, respectively.

(i) The substitution of a backup supplier is always a contingency measure. It has been noted that this substitution causes maximum variation in the value of the AQL (a 48.1% increase) that can lead to a negative impact on the quality control practices of the customers. The results also indicate that the relatively low risk performance of the backup supplier may cause a detrimental effect on the TVSP value of the supply chain network operation as well.

The comparison and analysis of the results indicates that a successful implementation of the decision support framework enables the supply chain network to achieve the performance target however in order to maintain a desired service level and to counter the possibility of a stock-out under the influence of probabilistic and network disruptions, the DMs have to allocate greater financial resources and be willing to accept substantial increase in transportation time and environmental impact.

6.2 Managerial Implications

The managerial implications of the research work presented in this thesis are included as below:

(a) Under network disruptions, supply chain service level can only be maintained at the expense of a significant increase in total cost.

(b) Lead time variation is a major contributor of increase in total transportation time.

(c) Supply chain disruptions always lead to an increase in the environmental impact.

(d) Low risk performance of a supplier has a negative impact on the total value of sustainable purchasing.

(e) Using backup suppliers may lead to major quality control issues in critical industry sectors i.e. pharmaceutical industry.

6.3 Research Limitations

The limitations of the research work included in the preceding chapters are as under:

(a) The take-make-dispose model offered by a linear supply chain is inherently at odds with the concept of sustainability. As most of the existing supply chains usually do not follow a closed loop model, the supply chain network considered for evaluation in this research work is a linear one.

(b) The single product, multiple customers approach adopted for developing the proposed decision support framework can limit its scope and range of application.

(c) The impact of quantity discounts and other similar incentives on the inventory control practices of the customers has not been incorporated in the MOMINLP mathematical model.

6.4 Future Work

Based on the development and results presented in the preceding chapters, some recommendations for future research have been included below:

(a) In future applications of the integrated methodology, new and improved sets of sustainability and resilience sub-criteria should be identified and used in the MCDM process either by conducting a literature review or an industry survey.

(b) The usefulness and potential of the proposed multi-phase, multi-period decision support framework can be further explored by extending its application to various other industry sectors i.e. electrical power generation and transmission, food production, processing and distribution, telecommunication networks infrastructure, or medical and surgical goods manufacturing industry etc.

(c) An interesting avenue for future research is the application of the proposed decision support framework to optimize a closed-loop supply chain network facing disruption risks.

(d) The case study presented in this research work employs a periodic review model to calculate a replenishment level for depleting inventory. As a future application of the decision support framework, different scenarios should be considered and evaluated where other categories or variations of inventory models with probabilistic demand have been used. The impact of using multiple probability distributions for describing demand can be incorporated in this analysis as well.

(e) The proposed decision support framework can only handle one product at any one time period considered. This issue can be addressed by modifying and improving the decision framework to incorporate multi-product scenarios.

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Appendix A

MCDM Analysis

1. **Calculation for Consistency Index**

- Combined Decision Matrix

	Economic	Environment	Social	Resilience
Economic	1.00	7.00	5.00	7.00
Environment	0.14	1.00	0.33	1.00
Social	0.20	3.00	1.00	1.00
Resilience	0.14	1.00	1.00	1.00
Sum	1.49	12.00	7.33	10.00

- Normalized Decision Matrix

	Economic	Environment	Social	Resilience
Economic	0.67	0.58	0.68	0.70
Environment	0.10	0.08	0.05	0.10
Social	0.13	0.25	0.14	0.10
Resilience	0.10	0.08	0.14	0.10

- Weight Matrix

Economic	0.66
Environment	0.08
Social	0.16
Resilience	0.10

- Weight Normalized Matrix

	Economic	Environment	Social	Resilience
Economic	0.66	0.57	0.78	0.73
Environment	0.09	0.08	0.05	0.10
Social	0.13	0.24	0.16	0.10
Resilience	0.09	0.08	0.16	0.10

- Eigen Value (λ_{max}) = 4.12
- Consistency Index = 0.04
- Consistency Ratio = 0.05

2. Calculation for Fuzzy E-AHP

(a) Calculation of Weights for TBL Sustainability & Resilience Criteria

- Combined Decision Matrix

	Economic	Environment	Social	Resilience
Economic	2.00	15.00	13.33	14.00
Environment	0.29	2.00	10.67	5.33
Social	0.38	0.87	2.00	9.67
Resilience	0.30	1.13	0.92	2.00

- Extended Normalized Fuzzy Decision Matrix

	$\boldsymbol{a}$	$\boldsymbol{n}$	$\boldsymbol{m}$
Economic	0.24	0.60	1.26
Environment	0.05	0.22	0.68
Social	0.06	0.13	0.47
Resilience	0.05	0.05	0.73

- Degree of Possibility

S1>S2	0.53
S1>S3	0.33
S1>S4	0.47
S2>S1	1.00
S2>S3	0.83
S2>S4	0.80
S3>S1	1.00
S3>S2	1.00

S3>S4	0.90
S4>S1	1.00
S4>S2	1.00
S4>S3	1.00

- Weight Vector

Economic	0.331
Environment	0.803
Social	0.896
Resilience	1.000

- Normalized Weight Vector

Economic	0.11
Environment	0.26
Social	0.30
Resilience	0.33

- Global Weights

Economic	0.602
Environment	0.193
Social	0.140
Resilience	0.065

(b) Calculation of Weights for Economic Sub-criteria

- Weight Matrix

Product Price	0.247
Payment Terms	0.189
Product Quality	0.136
Use of Technology	0.109
Volume Flexibility	0.067
Vendor's Reputation	0.066
Responsiveness	0.044
Product Mix	0.045
Past Business	0.097

- Extended Normalized Fuzzy Decision Matrix

	a	***n***	***m***
Product Price	0.06	0.20	0.54
Payment Terms	0.06	0.18	0.54
Product Quality	0.05	0.16	0.46
Use of Technology	0.05	0.14	0.40
Volume Flexibility	0.03	0.09	0.27
Vendor's Reputation	0.04	0.09	0.22
Responsiveness	0.02	0.05	0.14
Product Mix	0.02	0.04	0.08
Past Business	0.04	0.04	0.10

- Degree of Possibility

S1>S2	0.97	S4>S1	1.00	S7>S1	1.00

S1>S3	0.91	S4>S2	1.00	S7>S2	1.00
S1>S4	0.85	S4>S3	1.00	S7>S3	1.00
S1>S5	0.65	S4>S5	0.80	S7>S4	1.00
S1>S6	0.60	S4>S6	0.76	S7>S5	1.00
S1>S7	0.37	S4>S7	0.51	S7>S6	1.00
S1>S8	0.13	S4>S8	0.22	S7>S8	0.78
S1>S9	0.20	S4>S9	0.30	S7>S9	0.85
S2>S1	1.00	S5>S1	1.00	S8>S1	1.00
S2>S3	0.95	S5>S2	1.00	S8>S2	1.00
S2>S4	0.89	S5>S3	1.00	S8>S3	1.00
S2>S5	0.69	S5>S4	1.00	S8>S4	1.00
S2>S6	0.64	S5>S6	1.02	S8>S5	1.00
S2>S7	0.40	S5>S7	0.76	S8>S6	1.00
S2>S8	0.15	S5>S8	0.48	S8>S7	1.00
S2>S9	0.22	S5>S9	0.57	S8>S9	1.06
S3>S1	1.00	S6>S1	1.00	S9>S1	1.00
S3>S2	1.00	S6>S2	1.00	S9>S2	1.00
S3>S4	0.95	S6>S3	1.00	S9>S3	1.00
S3>S5	0.75	S6>S4	1.00	S9>S4	1.00
S3>S6	0.71	S6>S5	1.00	S9>S5	1.00
S3>S7	0.47	S6>S7	0.74	S9>S6	1.00
S3>S8	0.21	S6>S8	0.45	S9>S7	1.00
S3>S9	0.28	S6>S9	0.54	S9>S8	1.00

- Weight Vector

Product Price	0.132
Payment Terms	0.155
Product Quality	0.210
Use of Technology	0.220
Volume Flexibility	0.481
Vendor's Reputation	0.447
Responsiveness	0.783
Product Mix	1.000
Past Business	1.000

- Normalized Weight Vector

Product Price	0.03
Payment Terms	0.03
Product Quality	0.05
Use of Technology	0.05
Volume Flexibility	0.11
Vendor's Reputation	0.10
Responsiveness	0.18
Product Mix	0.23
Past Business	0.23

- Local Weights

Product Price	0.02
Payment Terms	0.02
Product Quality	0.03

Use of Technology	0.03
Volume Flexibility	0.07
Vendor's Reputation	0.07
Responsiveness	0.11
Product Mix	0.14
Past Business	0.14

(c) Calculation of Weights for Environment Sub-criteria

- Weight Matrix

Environmental Management System	0.510
Energy Consumption	0.248
Waste Management System	0.187
Innovative Capability	0.055

- Extended Normalized Fuzzy Decision Matrix

	a	***n***	***m***
Environmental Management System	0.13	0.47	1.32
Energy Consumption	0.07	0.32	0.93
Waste Management System	0.13	0.16	0.45
Innovative Capability	0.03	0.05	0.73

- Degree of Possibility

S1>S2	0.85
S1>S3	0.52
S1>S4	0.59
S2>S1	1.00

S2>S3	0.70
S2>S4	0.70
S3>S1	1.00
S3>S2	1.00
S3>S4	0.84
S4>S1	1.00
S4>S2	1.00
S4>S3	1.00

- Weight Vector

Environmental Management System	0.516
Energy Consumption	0.704
Waste Management System	0.836
Innovative Capability	1.000

- Normalized Weight Vector

Environmental Management System	0.17
Energy Consumption	0.23
Waste Management System	0.27
Innovative Capability	0.33

- Local Weights

Environmental Management System	0.01
Energy Consumption	0.02
Waste Management System	0.02
Innovative Capability	0.03

(d) Calculation of Weights for Social Sub-criteria

- Weight Matrix

Employee Health & Safety	0.593
Staff Personal & Technical Development	0.265
Information Disclosure	0.143

- Extended Normalized Fuzzy Decision Matrix

	a	***n***	***m***
Employee Health & Safety	0.09	0.63	2.03
Staff Personal & Technical Development	0.07	0.33	1.07
Information Disclosure	0.15	0.05	0.12

- Degree of Possibility

S1>S2	0.77
S1>S3	0.04
S2>S1	1.00
S2>S3	0.14
S3>S1	1.00
S3>S2	1.00

- Weight Vector

Employee Health & Safety	0.043
Staff Personal & Technical Development	0.141
Information Disclosure	1.000

- Normalized Weight Vector

Employee Health & Safety	0.04
Staff Personal & Technical Development	0.12
Information Disclosure	0.84

- Local Weights

Employee Health & Safety	0.01
Staff Personal & Technical Development	0.02
Information Disclosure	0.12

(e) Calculation of Weights for Resilience Sub-criteria

- Weight Matrix

Robustness	0.534
Agility	0.240
Leanness	0.170
Flexibility	0.056

- Extended Normalized Fuzzy Decision Matrix

	a	n	m
Robustness	0.13	0.49	1.45
Agility	0.09	0.28	0.96
Leanness	0.07	0.19	0.56
Flexibility	0.04	0.04	0.73

- Degree of Possibility

S1>S2	0.79

S1>S3	0.59
S1>S4	0.57
S2>S1	1.00
S2>S3	0.84
S2>S4	0.72
S3>S1	1.00
S3>S2	1.00
S3>S4	0.81
S4>S1	1.00
S4>S2	1.00
S4>S3	1.00

- Weight Vector

Robustness	0.566
Agility	0.724
Leanness	0.811
Flexibility	1.000

- Normalized Weight Vector

Robustness	0.18
Agility	0.23
Leanness	0.26
Flexibility	0.32

- Local Weights

Robustness	0.030

Agility	0.016
Leanness	0.016
Flexibility	0.030

3. Calculation for Fuzzy TOPSIS

(a) Calculation of Relative Closeness Matrix for TBL Sustainability & Resilience Criteria

- Combined Decision Matrix

	Economic	**Environment**	**Social**	**Resilience**
Supplier-1	0.69	0.12	0.36	0.15
Supplier-2	0.68	0.16	0.14	0.15
Supplier-3	0.64	0.23	0.54	0.92
Supplier-4	0.50	0.30	0.68	0.61
Supplier-5	0.20	0.87	0.86	0.42

- Normalized Combined Decision Matrix

	Economic	**Environment**	**Social**	**Resilience**
Supplier-1	0.54	0.12	0.28	0.13
Supplier-2	0.53	0.17	0.11	0.13
Supplier-3	0.50	0.24	0.42	0.77
Supplier-4	0.39	0.31	0.53	0.51
Supplier-5	0.16	0.90	0.67	0.35

- Weighted Normalized Combined Decision Matrix

	Economic	**Environment**	**Social**	**Resilience**
Supplier-1	0.32	0.02	0.04	0.01
Supplier-2	0.32	0.03	0.02	0.01
Supplier-3	0.30	0.05	0.06	0.05
Supplier-4	0.23	0.06	0.07	0.04
Supplier-5	0.09	0.17	0.09	0.02

- Positive Ideal (Best) & Negative Ideal (Worst) Solution

	Economic	**Environment**	**Social**	**Resilience**
Z+	0.32	0.17	0.09	0.05
Z-	0.09	0.02	0.02	0.01

- Euclidean Distances

	Sep+	**Sep-**
Supplier-1	0.175	0.231
Supplier-2	0.177	0.225
Supplier-3	0.261	0.217
Supplier-4	0.231	0.159
Supplier-5	0.273	0.167

- Closeness Coefficient Values

Supplier-1	0.570
Supplier-2	0.559
Supplier-3	0.553
Supplier-4	0.407
Supplier-5	0.380

(b) Calculation of Relative Closeness Matrix for Economic Criterion

- Combined Decision Matrix

	Product Price			**Payment Terms**			**Product Quality**		
Supplier-1	1	4.5	9	1	6.5	10	5	8	10
Supplier-2	1	5	9	1	6.5	10	5	8	10
Supplier-3	1	5	9	3	6.5	10	5	8	10
Supplier-4	1	4.5	9	3	7	10	3	7	10
Supplier-5	1	5	9	3	6.5	10	3	6.5	9
	Use of Technology			**Volume Flexibility**			**Vendor's Reputation**		
Supplier-1	3	7.5	10	3	7	10	5	8.5	10
Supplier-2	5	8	10	3	7	10	5	8.5	10
Supplier-3	3	7	10	3	6.5	9	5	7.5	10
Supplier-4	3	6	9	1	5.5	9	5	7.5	10
Supplier-5	1	6	9	3	6	9	3	7	10

	Responsiveness			Product Mix			Past Business		
Supplier-1	5	8	10	1	6	10	5	8.5	10
Supplier-2	5	8	10	1	6	10	5	8.5	10
Supplier-3	5	8	10	1	5.5	9	5	8	10
Supplier-4	5	8	10	1	5.5	9	3	7	10
Supplier-5	5	8	10	1	5.5	9	1	6.5	10

- Normalized Combined Decision Matrix

	Product Price			Payment Terms			Product Quality		
Supplier-1	0.03	0.15	0.30	0.03	0.22	0.34	0.17	0.27	0.34
Supplier-2	0.03	0.17	0.30	0.03	0.22	0.34	0.17	0.27	0.34
Supplier-3	0.03	0.17	0.31	0.10	0.22	0.34	0.17	0.28	0.34
Supplier-4	0.03	0.16	0.31	0.10	0.24	0.35	0.10	0.24	0.35
Supplier-5	0.04	0.17	0.31	0.10	0.22	0.34	0.10	0.22	0.31

	Use of Technology			**Volume Flexibility**			**Vendor's Reputation**		
Supplier-1	0.10	0.25	0.34	0.10	0.24	0.34	0.17	0.29	0.34
Supplier-2	0.17	0.27	0.34	0.10	0.24	0.34	0.17	0.29	0.34
Supplier-3	0.10	0.24	0.34	0.10	0.22	0.31	0.17	0.26	0.34
Supplier-4	0.10	0.21	0.31	0.03	0.19	0.31	0.17	0.26	0.35
Supplier-5	0.03	0.21	0.31	0.10	0.21	0.31	0.10	0.24	0.34
	Responsiveness			**Product Mix**			**Past Business**		
Supplier-1	0.17	0.27	0.34	0.03	0.20	0.34	0.17	0.29	0.34
Supplier-2	0.17	0.27	0.34	0.03	0.20	0.34	0.17	0.29	0.34
Supplier-3	0.17	0.28	0.34	0.03	0.19	0.31	0.17	0.28	0.34
Supplier-4	0.17	0.28	0.35	0.03	0.19	0.31	0.10	0.24	0.35
Supplier-5	0.17	0.28	0.34	0.03	0.19	0.31	0.03	0.22	0.34

- Weighted Normalized Combined Decision Matrix

	Product Price			**Payment Terms**			**Product Quality**		
Supplier-1	0.002	0.030	0.164	0.002	0.039	0.182	0.008	0.043	0.155
Supplier-2	0.002	0.034	0.164	0.002	0.039	0.182	0.008	0.043	0.155
Supplier-3	0.002	0.034	0.167	0.006	0.040	0.186	0.009	0.044	0.158
Supplier-4	0.002	0.031	0.169	0.006	0.044	0.188	0.005	0.039	0.160
Supplier-5	0.002	0.034	0.167	0.006	0.040	0.186	0.005	0.036	0.143

	Use of Technology			**Volume Flexibility**			**Vendor's Reputation**		
Supplier-1	0.005	0.035	0.135	0.003	0.021	0.091	0.007	0.026	0.074
Supplier-2	0.008	0.038	0.135	0.003	0.021	0.091	0.007	0.026	0.074
Supplier-3	0.005	0.034	0.138	0.003	0.020	0.084	0.007	0.023	0.076
Supplier-4	0.005	0.029	0.125	0.001	0.017	0.085	0.007	0.024	0.077
Supplier-5	0.002	0.029	0.124	0.003	0.019	0.084	0.004	0.022	0.076

	Responsiveness			**Product Mix**			**Past Business**		
Supplier-1	0.003	0.013	0.047	0.001	0.008	0.027	0.007	0.011	0.034
Supplier-2	0.003	0.013	0.047	0.001	0.008	0.027	0.007	0.011	0.034
Supplier-3	0.003	0.014	0.048	0.001	0.008	0.025	0.007	0.011	0.034
Supplier-4	0.003	0.014	0.049	0.001	0.008	0.025	0.004	0.010	0.035
Supplier-5	0.003	0.014	0.048	0.001	0.008	0.025	0.001	0.009	0.034

- Positive Ideal (Best) & Negative Ideal (Worst) Solution

	Product Price			**Payment Terms**			**Product Quality**		
Z+	0.002	0.030	0.164	0.006	0.044	0.188	0.009	0.044	0.160
Z-	0.002	0.034	0.169	0.002	0.039	0.182	0.005	0.036	0.143
	Use of Technology			**Volume Flexibility**			**Vendor's Reputation**		
Z+	0.008	0.038	0.138	0.003	0.021	0.091	0.007	0.026	0.077
Z-	0.002	0.029	0.124	0.001	0.017	0.084	0.004	0.022	0.074

	Responsiveness			Product Mix			Past Business		
Z+	0.003	0.014	0.049	0.001	0.008	0.027	0.007	0.011	0.035
Z-	0.003	0.013	0.047	0.001	0.008	0.025	0.001	0.009	0.034

- Euclidean Distances

	Sep+	**Sep-**
Supplier-1	0.014	0.031
Supplier-2	0.015	0.032
Supplier-3	0.017	0.031
Supplier-4	0.024	0.024
Supplier-5	0.040	0.010

- Closeness Coefficient Values

Supplier-1	0.69
Supplier-2	0.68

Supplier-3	0.64
Supplier-4	0.50
Supplier-5	0.20

(c) Calculation of Relative Closeness Matrix for Environment Criterion

- Combined Decision Matrix

	Environmental Management System			**Energy Consumption**		
Supplier-1	3	7	10	3	7.5	10
Supplier-2	3	7	10	3	7	10
Supplier-3	3	5.5	9	3	6.5	9
Supplier-4	3	5.5	9	3	6	9
Supplier-5	1	4.5	9	1	5	9
	Waste Management System			**Innovative Capability**		
Supplier-1	1	5.5	10	3	7.5	10
Supplier-2	1	5.5	10	3	7.5	10

Supplier-3	1	5.5	9	3	7	10
Supplier-4	1	5.5	9	3	7	10
Supplier-5	1	5	9	1	6.5	10

- Normalized Combined Decision Matrix

		Environmental Management System			**Energy Consumption**	
Supplier-1	0.217	0.506	0.722	0.217	0.542	0.722
Supplier-2	0.221	0.515	0.736	0.221	0.515	0.736
Supplier-3	0.244	0.446	0.731	0.244	0.528	0.731
Supplier-4	0.249	0.456	0.746	0.249	0.497	0.746
Supplier-5	0.094	0.424	0.849	0.094	0.471	0.849
		Waste Management System			**Innovative Capability**	
Supplier-1	0.072	0.397	0.722	0.217	0.542	0.722
Supplier-2	0.074	0.405	0.736	0.221	0.552	0.736

Supplier-3	0.081	0.446	0.731	0.244	0.568	0.812
Supplier-4	0.083	0.456	0.746	0.249	0.580	0.829
Supplier-5	0.094	0.471	0.849	0.094	0.613	0.943

- Weighted Normalized Combined Decision Matrix

	Environmental Management System			**Energy Consumption**		
Supplier-1	0.028	0.238	0.953	0.015	0.173	0.672
Supplier-2	0.029	0.242	0.972	0.015	0.165	0.685
Supplier-3	0.032	0.210	0.964	0.017	0.169	0.679
Supplier-4	0.032	0.214	0.985	0.017	0.159	0.694
Supplier-5	0.012	0.199	1.120	0.007	0.151	0.789
	Waste Management System			**Innovative Capability**		
Supplier-1	0.009	0.064	0.325	0.006	0.027	0.527
Supplier-2	0.010	0.065	0.331	0.007	0.028	0.537

Supplier-3	0.011	0.071	0.329	0.007	0.028	0.593
Supplier-4	0.011	0.073	0.336	0.007	0.029	0.605
Supplier-5	0.012	0.075	0.382	0.003	0.031	0.688

- Positive Ideal (Best) & Negative Ideal (Worst) Solution

	Environmental Management System			**Energy Consumption**		
Z+	0.032	0.242	1.120	0.017	0.173	0.789
Z-	0.012	0.199	0.953	0.007	0.151	0.672
	Waste Management System			**Innovative Capability**		
Z+	0.012	0.075	0.382	0.007	0.031	0.688
Z-	0.009	0.064	0.325	0.003	0.027	0.527

- Euclidean Distances

	Sep+	**Sep-**
Supplier-1	0.291	0.040
Supplier-2	0.263	0.051
Supplier-3	0.241	0.070
Supplier-4	0.210	0.092
Supplier-5	0.044	0.291

- Closeness Coefficient Values

Supplier-1	0.12
Supplier-2	0.16
Supplier-3	0.23
Supplier-4	0.30
Supplier-5	0.87

(d) Calculation of Relative Closeness Matrix for Social Criterion

- Combined Decision Matrix

	Employee Health & Safety			**Staff Personal & Technical Development**			**Information Disclosure**		
Supplier-1	3	8	10	5	7.5	10	1	5.5	10
Supplier-2	7	9	10	5	7.5	10	1	6	10
Supplier-3	5	7.5	10	5	7	9	1	5	9
Supplier-4	3	7	10	5	7	9	1	5	9
Supplier-5	1	6	10	5	7	9	1	5	9

- Normalized Combined Decision Matrix

	Employee Health & Safety			**Staff Personal & Technical Development**			**Information Disclosure**		
Supplier-1	0.245	0.652	0.815	0.408	0.611	0.815	0.082	0.448	0.815
Supplier-2	0.532	0.684	0.760	0.380	0.570	0.760	0.076	0.456	0.760
Supplier-3	0.438	0.657	0.876	0.438	0.613	0.789	0.088	0.438	0.789
Supplier-4	0.271	0.631	0.902	0.451	0.631	0.812	0.090	0.451	0.812

Supplier-5	0.095	0.572	0.953	0.477	0.667	0.858	0.095	0.477	0.858

- Weighted Normalized Combined Decision Matrix

	Employee Health & Safety			**Staff Personal & Technical Development**			**Information Disclosure**		
Supplier-1	0.022	0.411	1.655	0.029	0.202	0.872	0.012	0.022	0.098
Supplier-2	0.048	0.431	1.542	0.027	0.188	0.813	0.011	0.023	0.091
Supplier-3	0.039	0.414	1.779	0.031	0.202	0.844	0.013	0.022	0.095
Supplier-4	0.024	0.398	1.830	0.032	0.208	0.868	0.014	0.023	0.097
Supplier-5	0.009	0.360	1.936	0.033	0.220	0.918	0.014	0.024	0.103

- Positive Ideal (Best) & Negative Ideal (Worst) Solution

	Employee Health & Safety			**Staff Personal & Technical Development**			**Information Disclosure**		
Z+	0.048	0.431	1.936	0.033	0.220	0.918	0.014	0.024	0.103
Z-	0.009	0.360	1.542	0.027	0.188	0.813	0.011	0.022	0.091

- Euclidean Distances

	Sep+	**Sep-**
Supplier-1	0.195	0.111
Supplier-2	0.298	0.047
Supplier-3	0.140	0.163
Supplier-4	0.098	0.206
Supplier-5	0.047	0.298

- Closeness Coefficient Values

Supplier-1	0.36
Supplier-2	0.14
Supplier-3	0.54
Supplier-4	0.68
Supplier-5	0.86

(e) Calculation of Relative Closeness Matrix for Resilience Criterion

- Combined Decision Matrix

	Robustness			**Agility**			**Leanness**			**Flexibility**		
Supplier-1	1	5.5	9	1	5.5	9	1	6.5	10	3	7	10
Supplier-2	1	5.5	9	1	5.5	9	1	6.5	10	3	7	10
Supplier-3	1	5.5	9	1	5	9	1	5.5	9	3	6.5	10
Supplier-4	1	5	9	1	5.5	9	1	5.5	9	3	7	10
Supplier-5	1	5.5	9	1	5.5	9	1	5.5	9	3	7	10

- Normalized Combined Decision Matrix

	Robustness			**Agility**			**Leanness**			**Flexibility**		
Supplier-1	0.081	0.446	0.731	0.081	0.446	0.731	0.081	0.528	0.812	0.244	0.568	0.812
Supplier-2	0.081	0.446	0.731	0.081	0.446	0.731	0.081	0.528	0.812	0.244	0.568	0.812
Supplier-3	0.088	0.487	0.796	0.088	0.442	0.796	0.088	0.487	0.796	0.265	0.575	0.885
Supplier-4	0.086	0.431	0.776	0.086	0.474	0.776	0.086	0.474	0.776	0.259	0.604	0.862

Supplier-5	0.085	0.465	0.761	0.085	0.465	0.761	0.085	0.465	0.761	0.254	0.592	0.846

- Weighted Normalized Combined Decision Matrix

	Robustness			**Agility**			**Leanness**			**Flexibility**		
Supplier-1	0.011	0.219	1.059	0.007	0.125	0.701	0.006	0.100	0.455	0.010	0.023	0.593
Supplier-2	0.011	0.219	1.059	0.007	0.125	0.701	0.006	0.100	0.455	0.010	0.023	0.593
Supplier-3	0.012	0.238	1.155	0.008	0.124	0.764	0.006	0.092	0.446	0.011	0.023	0.646
Supplier-4	0.011	0.211	1.125	0.008	0.133	0.745	0.006	0.090	0.435	0.010	0.024	0.629
Supplier-5	0.011	0.228	1.104	0.008	0.130	0.731	0.006	0.088	0.426	0.010	0.024	0.618

- Positive Ideal (Best) & Negative Ideal (Worst) Solution

	Robustness			**Agility**			**Leanness**			**Flexibility**		
Z+	0.012	0.238	1.155	0.008	0.133	0.764	0.006	0.100	0.455	0.011	0.024	0.646
Z-	0.011	0.211	1.059	0.007	0.124	0.701	0.006	0.088	0.426	0.010	0.023	0.593

- Euclidean Distances

	Sep+	**Sep-**
Supplier-1	0.124	0.023
Supplier-2	0.124	0.023
Supplier-3	0.013	0.136
Supplier-4	0.057	0.090
Supplier-5	0.083	0.059

- Closeness Coefficient Values

Supplier-1	0.15
Supplier-2	0.15
Supplier-3	0.92
Supplier-4	0.61
Supplier-5	0.42

4. Calculation for Sensitivity Analysis

- Sub-criteria Weights from FE-AHP

	a	***n***	***m***
	Current Case		
Product Price	0.06	0.20	0.54
Payment Terms	0.06	0.18	0.54
Responsiveness	0.02	0.05	0.14
Vendor's Reputation	0.04	0.09	0.22
Environmental Management System	0.13	0.47	1.32
Innovative Capability	0.03	0.05	0.73
Information Disclosure	0.15	0.05	0.12
Flexibility	0.04	0.04	0.73

- Variations in Sub-criteria Weights from FE-AHP

	a	**n**	**m**	**a**	**n**	**m**	**a**	**n**	**m**
	Case 1			**Case 2**			**Case 3**		
Product Price	0.057	0.197	0.537	0.053	0.193	0.533	0.050	0.190	0.530
Payment Terms	0.057	0.177	0.537	0.053	0.173	0.533	0.050	0.170	0.530
Responsiveness	0.018	0.047	0.137	0.015	0.043	0.133	0.013	0.040	0.130
Vendor's Reputation	0.037	0.087	0.217	0.033	0.083	0.213	0.030	0.080	0.210
Environmental Management System	0.134	0.474	1.324	0.137	0.477	1.327	0.141	0.481	1.331
Innovative Capability	0.034	0.054	0.734	0.037	0.057	0.737	0.041	0.061	0.741
Information Disclosure	0.154	0.054	0.124	0.157	0.057	0.127	0.161	0.061	0.131
Flexibility	0.044	0.734	0.734	0.047	0.737	0.737	0.051	0.741	0.741
	Case 4			**Case 5**			**Case 6**		
Product Price	0.046	0.186	0.526	0.043	0.183	0.523	0.039	0.179	0.519
Payment Terms	0.046	0.166	0.526	0.043	0.163	0.523	0.039	0.159	0.519

Responsiveness	0.010	0.036	0.126	0.008	0.033	0.123	0.005	0.029	0.119
Vendor's Reputation	0.026	0.076	0.206	0.023	0.073	0.203	0.019	0.069	0.199
Environmental Management System	0.144	0.484	1.334	0.148	0.488	1.338	0.151	0.491	1.341
Innovative Capability	0.044	0.064	0.744	0.048	0.068	0.748	0.051	0.071	0.751
Information Disclosure	0.164	0.064	0.134	0.168	0.068	0.138	0.171	0.071	0.141
Flexibility	0.054	0.744	0.744	0.058	0.748	0.748	0.061	0.751	0.751

- Relative Closeness Coefficient Values from FTOPSIS

	Economic	**Environment**	**Social**	**Resilience**
	Current Case			
Supplier-1	0.69	0.12	0.36	0.15
Supplier-2	0.68	0.16	0.14	0.15
Supplier-3	0.64	0.23	0.54	0.92
Supplier-4	0.50	0.30	0.68	0.61
Supplier-5	0.20	0.87	0.86	0.42

- Variations in Relative Closeness Coefficient Values from FTOPSIS

	Economic	Environment	Social	Resilience	Economic	Environment	Social	Resilience
	Case 1				Case 2			
Supplier-1	0.69	0.12	0.36	0.15	0.69	0.12	0.36	0.15
Supplier-2	0.68	0.16	0.14	0.15	0.68	0.16	0.14	0.15
Supplier-3	0.64	0.23	0.54	0.85	0.65	0.23	0.54	0.85
Supplier-4	0.50	0.30	0.68	0.63	0.50	0.31	0.68	0.63
Supplier-5	0.20	0.87	0.86	0.43	0.32	0.87	0.87	0.43
	Case 3				Case 4			
Supplier-1	0.69	0.12	0.36	0.15	0.69	0.12	0.36	0.15
Supplier-2	0.69	0.16	0.14	0.15	0.69	0.16	0.14	0.15
Supplier-3	0.65	0.23	0.54	0.85	0.65	0.23	0.54	0.85
Supplier-4	0.49	0.31	0.68	0.63	0.49	0.31	0.68	0.63
Supplier-5	0.19	0.86	0.87	0.43	0.18	0.86	0.87	0.43

	Case 5				Case 6			
Supplier-1	0.70	0.13	0.36	0.15	0.70	0.13	0.36	0.15
Supplier-2	0.69	0.17	0.14	0.15	0.69	0.17	0.14	0.15
Supplier-3	0.65	0.23	0.54	0.85	0.65	0.23	0.54	0.85
Supplier-4	0.49	0.31	0.68	0.63	0.49	0.31	0.68	0.63
Supplier-5	0.18	0.86	0.87	0.43	0.18	0.86	0.87	0.43

- Sensitivity Analysis Results

	Current Case	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**
Supplier-1	0.57	0.57	0.50	0.57	0.58	0.58	0.58
Supplier-2	0.56	0.56	0.49	0.57	0.57	0.57	0.58
Supplier-3	0.55	0.56	0.59	0.56	0.57	0.57	0.57
Supplier-4	0.41	0.40	0.32	0.40	0.41	0.41	0.41
Supplier-5	0.38	0.38	0.42	0.37	0.37	0.37	0.37

Appendix B

Risk Criteria Weights

- Resilience Sub-criteria Weights from E-AHP

Robustness	0.183
Agility	0.233
Leanness	0.262
Flexibility	0.322

- Resilience Sub-criteria Scores from DMs

	Robustness	**Agility**	**Leanness**	**Flexibility**
Supplier-1	5	5	3	5
Supplier-2	7	5	3	5
Supplier-3	7	5	3	5
Supplier-4	5	7	3	7
Supplier-5	7	7	3	7
Sum	31	29	15	29

- Normalized Values

Supplier-1	0.16	0.17	0.20	0.17
Supplier-2	0.23	0.17	0.20	0.17
Supplier-3	0.23	0.17	0.20	0.17
Supplier-4	0.16	0.24	0.20	0.24
Supplier-5	0.23	0.24	0.20	0.24

- Risk Expectation Value (R_s)

	$\boldsymbol{R_s}$
Supplier-1	0.18
Supplier-2	0.19
Supplier-3	0.19
Supplier-4	0.22
Supplier-5	0.23

- Risk Weights of Suppliers

	$\boldsymbol{w}$
Supplier-1	0.18
Supplier-2	0.19
Supplier-3	0.19
Supplier-4	0.22
Supplier-5	0.23

Appendix C

Input Data

- No. of suppliers = 03
- No. of ports = 02
- No. of warehouses = 03
- No. of customers = 02
- No. of transportation modes = 03 (Sea, Rail, Road)
- Purchasing cost for each supplier (\$/kg)

  ${C_p}^1$ = 0.68, 0.715, 0.76

  ${C_p}^2$ = 0.79, 0.825, 0.87

  ${C_p}^3$ = 0.65, 0.695, 0.73
- Ordering cost for each supplier (\$)

  O_1 = 156.2, 158.2, 160.2

  O_2 = 140.7, 142.7, 144.7

  O_3 = 163.8, 165.8, 167.8
- Inventory holding cost (\$/kg)

  H_o = 0.026, 0.036, 0.046
- Transportation cost (\$/km)

  TC_{Sea} = 0.21, 0.41, 0.61

  TC_{Rail} = 0.53, 0.73, 0.93

  TC_{Road} = 0.75, 0.95, 1.15
- Transfer cost matrix (\$/kg): TrC_{mn} = Transfer cost from mode "m" to mode "n"

	Sea	Rail	Road
Sea	1.2	0.9	0.7
Rail	0.9	1.0	1.1
Road	0.7	1.1	0.6

- Custom clearance cost ($/kg): CC_{ij} = Custom clearance cost while moving from supplier "i" to port "j"
  $CC_{11} = 1.15 \times C_p{}^1$
  $CC_{21} = 1.15 \times C_p{}^2$
  $CC_{31} = 1.15 \times C_p{}^3$
- Transfer time matrix (h/Container): TrT_{mn} = Transfer time from mode "m" to mode "n"

	Sea	Rail	Road
Sea	0.7	0.17	0.17
Rail	0.17	0.4	0.12
Road	0.17	0.12	0.1

- Custom clearance time (h/Container): CCT_{ij} = Custom clearance time from supplier "i" to port "j"
  $CCT_{11} = 4$
  $CCT_{21} = 4$
  $CCT_{31} = 4$
- Maximum capacity of supplier "i" (kg): S_i = Maximum capacity of i^{th} supplier
  S_1 = 24,00,00, 26,00,00, 28,00,00
  S_2 = 23,00,00, 25,00,00, 27,00,00
  S_3 = 21,00,00, 23,00,00, 25,00,00
- Capacity of warehouse "k" (kg): $CAPw_k$ = Capacity of k^{th} warehouse
  $CAPw_1$ = 30,50,00, 32,50,00, 34,50,00
  $CAPw_2$ = 34,50,00, 36,50,00, 38,50,00
  $CAPw_3$ = 38,50,00, 40,50,00, 42,50,00

- Velocity of mode "m": (Adapted from [145])

Mode	Velocity (km/h)
Sea	35
Rail	60
Road	90

- Capacity of mode "m":

Mode	Capacity/Carrier (kg)
Sea	250,000,000
Rail	300,000
Road	20,000

For logistic decisions, it is considered that New-Panamax ship has an average capacity of 12,500 Twenty-foot Equivalent Units (TEUs)[1] while 15 TEUs each having a capacity of 800 bags (25 kg/bag) per container are permissible for each train.

- CO_2 emissions (gm/km) (Adapted from [43])

For Sea: 6.04

For Rail: 17

For Road: 50

- Demand of customers (kg)

D_1 = 22,75,00, 24,00,00, 25,35,00

D_2 = 32,20,00, 35,00,00, 37,50,00

(Q1 demand values included as exemplar to illustrate the fuzzification of demand data.)

- Acceptable quality limit of supplier "i" (kg)

$\alpha_1 = 0.04$

$\alpha_2 = 0.04$

$\alpha_3 = 0.03$

[1]https://transportgeography.org/

Appendix D

MCDM for OA Results

1. **Calculation for CRITIC Weights**

   - Normalized Decision Matrix

	f_1	f_2	f_3	f_4	f_5
1	0.23	0.90	0.91	0.88	0.26
2	0.45	1.00	1.00	0.91	0.18
3	1.00	0.75	0.78	1.00	0.00
4	0.54	0.69	0.73	0.53	0.47
5	0.31	0.73	0.78	0.88	0.24
6	0.46	0.98	0.97	0.50	0.50
7	0.24	0.81	0.84	0.50	0.56
8	0.48	0.00	0.00	0.50	0.50
9	0.51	0.81	0.84	0.50	0.50
10	0.23	0.78	0.81	0.50	0.56
11	0.48	0.80	0.83	0.50	0.50
12	0.00	0.75	0.77	0.00	1.00
13	0.29	0.70	0.73	0.50	0.55
14	0.00	0.79	0.80	0.00	1.00

15	0.00	0.73	0.75	0.00	1.00
16	0.00	0.79	0.80	0.00	1.00
17	0.00	0.73	0.75	0.00	1.00
18	0.00	0.75	0.77	0.00	1.00
19	0.00	0.76	0.78	0.00	1.00
20	0.00	0.79	0.80	0.00	1.00
Standard Deviation	0.27	0.20	0.20	0.36	0.33

- Symmetric Matrix

	f_1	f_2	f_3	f_4	f_5
f_1	1.00	-0.09	-0.08	0.81	-0.87
f_2	-0.09	1.00	1.00	0.08	-0.05
f_3	-0.08	1.00	1.00	0.10	-0.07
f_4	0.81	0.08	0.10	1.00	-0.99
f_5	-0.87	-0.05	-0.07	-0.99	1.00

- Conflict Measurement

	f_1	f_2	f_3	f_4	f_5	**Sum**
f_1	0.00	1.09	1.08	0.19	1.87	4.22
f_2	1.09	0.00	0.00	0.92	1.05	3.07
f_3	1.08	0.00	0.00	0.90	1.07	3.05
f_4	0.19	0.92	0.90	0.00	1.99	4.00
f_5	1.87	1.05	1.07	1.99	0.00	5.99

- Quality of Information

f_1	1.15
f_2	0.60
f_3	0.60
f_4	1.43
f_5	1.99
Sum	5.76

- Objective Weights

f_1	0.21
f_2	0.10
f_3	0.10
f_4	0.25
f_5	0.34

(The CRITIC weights have been determined in the preceding tables using Q1 data as exemplar to illustrate the calculation procedure. Similar procedure has been followed for calculating CRITIC weights for the remaining three quarters.)

2. Calculation for TOPSIS Augmented with CRITIC Weights

- Normalized Decision Matrix

	f_1	f_2	f_3	f_4	f_5
1	0.223655	0.206637	0.183649	0.217831	0.213605
2	0.223266	0.195232	0.162620	0.217416	0.211730
3	0.222287	0.222441	0.217232	0.216368	0.206987
4	0.223110	0.229085	0.229214	0.221852	0.219026
5	0.223526	0.224965	0.216554	0.217723	0.213138
6	0.223248	0.197221	0.169366	0.222223	0.219840
7	0.223653	0.216423	0.201930	0.222223	0.221319
8	0.223218	0.305998	0.407058	0.222223	0.219840
9	0.223157	0.216539	0.201937	0.222223	0.219840
10	0.223655	0.219338	0.208614	0.222223	0.221319
11	0.223219	0.217513	0.204651	0.222223	0.219840
12	0.224068	0.222904	0.219971	0.228079	0.232693
13	0.223563	0.228883	0.229200	0.222223	0.221020
14	0.224072	0.218466	0.211943	0.228079	0.232693
15	0.224073	0.224861	0.224610	0.228079	0.232693
16	0.224072	0.218466	0.211943	0.228079	0.232693
17	0.224073	0.224861	0.224610	0.228079	0.232693
18	0.224068	0.222655	0.219428	0.228079	0.232693
19	0.224070	0.221316	0.217113	0.228079	0.232693
20	0.224072	0.218466	0.211943	0.228079	0.232693

- Weighted Normalized Decision Matrix

	f_1	f_2	f_3	f_4	f_5
1	0.044731	0.020664	0.018365	0.054458	0.072626
2	0.044653	0.019523	0.016262	0.054354	0.071988
3	0.044457	0.022244	0.021723	0.054092	0.070376
4	0.044622	0.022908	0.022921	0.055463	0.074469
5	0.044705	0.022496	0.021655	0.054431	0.072467
6	0.044650	0.019722	0.016937	0.055556	0.074746
7	0.044731	0.021642	0.020193	0.055556	0.075248
8	0.044644	0.030600	0.040706	0.055556	0.074746
9	0.044631	0.021654	0.020194	0.055556	0.074746
10	0.044731	0.021934	0.020861	0.055556	0.075248
11	0.044644	0.021751	0.020465	0.055556	0.074746
12	0.044814	0.022290	0.021997	0.057020	0.079115
13	0.044713	0.022888	0.022920	0.055556	0.075147
14	0.044814	0.021847	0.021194	0.057020	0.079115
15	0.044815	0.022486	0.022461	0.057020	0.079115
16	0.044814	0.021847	0.021194	0.057020	0.079115
17	0.044815	0.022486	0.022461	0.057020	0.079115
18	0.044814	0.022265	0.021943	0.057020	0.079115
19	0.044814	0.022132	0.021711	0.057020	0.079115
20	0.044814	0.021847	0.021194	0.057020	0.079115
V+	0.044457	0.019523	0.016262	0.054092	0.070376
V-	0.044815	0.030600	0.040706	0.057020	0.079115

- Euclidean Distance

	S+	**S-**
1	0.003316	0.025427
2	0.001645	0.027895
3	0.006101	0.022699
4	0.008629	0.019987
5	0.006517	0.021897
6	0.004666	0.026544
7	0.006775	0.022762
8	0.027230	0.004612
9	0.006424	0.022848
10	0.007275	0.022045
11	0.006626	0.022567
12	0.011209	0.020471
13	0.008979	0.019842
14	0.010715	0.021385
15	0.011502	0.019968
16	0.010715	0.021385
17	0.011502	0.019968
18	0.011175	0.020531
19	0.011026	0.020797
20	0.010715	0.021385

- Performance Score

	S-/(S+S-)
1	0.944
2	0.885
3	0.851
4	0.788
5	0.771
6	0.698
7	0.771
8	0.145
9	0.781
10	0.752
11	0.773
12	0.646
13	0.688
14	0.666
15	0.635
16	0.666
17	0.635
18	0.648
19	0.654
20	0.666
Max	0.944
Min	0.145

(TOPSIS has been implemented in the preceding tables using Q1 data as exemplar to illustrate the calculation procedure. Similar procedure has been followed for ranking the best Pareto optimal solutions for the remaining three quarters.)

Appendix E

05 Years Demand Data

Quarter	**D1 (kg) [25 kg Bag]**	**D2 (kg) [25 kg Bag]**	**D1+D2 (kg) [25 kg Bag]**
Jan-Mar, 2018	97000 [3880]	276950 [11078]	373950 [14958]
Apr-Jun, 2018	163000 [6520]	203900 [8156]	366900 [14676]
Jul-Sep, 2018	110000 [4400]	192150 [7686]	302150 [12086]
Oct-Dec, 2018	153000 [6120]	246000 [9840]	399000 [15960]
Jan-Mar, 2019	56000 [2240]	275000 [11000]	331000 [13240]
Apr-Jun, 2019	191000 [7640]	178000 [7120]	369000 [14760]
Jul-Sep, 2019	175000 [7000]	190000 [7600]	365000 [14600]
Oct-Dec, 2019	184000 [7360]	254000 [10160]	438000 [17520]
Jan-Mar, 2020	198500 [7940]	225400 [9016]	423900 [16956]
Apr-Jun, 2020	136000 [5440]	60000 [2400]	196000 [7840]
Jul-Sep, 2020	20000 [800]	50000 [2000]	70000 [2800]
Oct-Dec, 2020	24000 [960]	49000 [1960]	73000 [2920]

Jan-Mar, 2021	85150 [3406]	149800 [5992]	234950 [9398]
Apr-Jun, 2021	152900 [6116]	193000 [7720]	345900 [13836]
Jul-Sep, 2021	134000 [5360]	195500 [7820]	329500 [13180]
Oct-Dec, 2021	130000 [5200]	196640 [7866]	326640 [13066]
Jan-Mar, 2022	240000 [9600]	350000 [14000]	590000 [23600]
Apr-Jun, 2022	226500 [9060]	375500 [15020]	602000 [24080]
Jul-Sep, 2022	238000 [9520]	322000 [12880]	560000 [22400]
Oct-Dec, 2022	229000 [9160]	356000 [14240]	585000 [23400]
Jan-Mar, 2023	150200 [6008]	251100 [10044]	401300 [16052]
Average	147297.62 [5892]	218568.57 [8743]	365866.19 [14635]
Standard Deviation	65139.51 [2606]	93079.73 [3723]	146720.91 [5869]

Appendix F

Critical Node & Link Analysis

- Calculation of s_{ji}

	S1	S2	S3	P1	P2	W1	W2	W3	C1	C2
S1	0	0	0	0.364	0	0	0	0	0	0
S2		0	0	0.399	0	0	0	0	0	0
S3			0	0.235	0.388	0	0	0	0	0
P1				0	0.611	0.964	0.934	0.872	0	0
P2					0	0.035	0.065	0.127	0	0
W1						0	0	0	0.266	0.531
W2							0	0	0.661	0.163
W3								0	0.071	0.304
C1									0	0
C2										0
Sum	0	0	0	0.998	0.999	0.999	0.999	0.999	0.998	0.998

In the above table, the variable S represents suppliers, P represents ports, W represents warehouses, and C represents customers, respectively.

- Calculation of p_j^2

	S1	S2	S3	P1	P2	W1	W2	W3	C1	C2
S1	0	0	0	0.12603	0	0	0	0	0	0
S2	0	0	0	0.15132	0	0	0	0	0	0
S3	0	0	0	0.05244	0.00068	0	0	0	0	0
P1	0	0	0	0	0.00168	0.16728	0.11628	0.03386	0	0
P2	0	0	0	0	0	0.00023	0.00058	0.00073	0	0
W1	0	0	0	0	0	0	0	0	0.01166	0.09986
W2	0	0	0	0	0	0	0	0	0.07182	0.00941
W3	0	0	0	0	0	0	0	0	0.00084	0.03276
C1	0	0	0	0	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0	0

- Calculation of SCI_j

	S1	S2	S3	P1	P2	W1	W2	W3	C1	C2
S1	0	0	0	0.04587	0	0	0	0	0	0
S2	0	0	0	0.06038	0	0	0	0	0	0
S3	0	0	0	0.01232	0.00026	0	0	0	0	0
P1	0	0	0	0	0.00103	0.16126	0.10861	0.02952	0	0
P2	0	0	0	0	0	0.0000079	0.000037	0.000093	0	0
W1	0	0	0	0	0	0	0	0	0.0031	0.05302
W2	0	0	0	0	0	0	0	0	0.04748	0.00153
W3	0	0	0	0	0	0	0	0	0.00006	0.00996
C1	0	0	0	0	0	0	0	0	0	0
C2	0	0	0	0	0	0	0	0	0	0
Sum	0	0	0	0.11857	0.00129	0.16127	0.10864	0.02962	0.05064	0.06452

(SCI has been determined in the above table using Q1 data as exemplar to illustrate the calculation procedure. Similar procedure has been followed for calculating SCI values for the remaining three quarters.)