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Development of the supply chain and production management system (SCPMS) for small-series fashion industry

Nitin Harale

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Par

Nitin HARALE

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Presented in view to obtain the degree of

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In

Specialty: Automation, Computer Engineering, Signal and Image Processing

by

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Small-series Fashion Industry**

Defended on 28th January 2021

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Abbreviations

SCM – Supply Chain Management

SC – Supply Chain

IoT – Internet of Things

AI – Artificial Intelligence

IoT – Internet of Things

MTO – Make-to-order

MCDM – Multi-criteria Decision Method

AHP – Analytic hierarchy process

TOPSIS – Technique for Order of Preference by similarity to Ideal solution

kNN – k Nearest neighbours

NB – Naïve Bayes

RF – Random forest

NN – Neural network

AUC – Area under the Curve

CA – Classification accuracy

EA – Evolutionary algorithm

OR – Operation research

GA – Genetic Algorithm

JIT – Just in time

TFN – Triangular Fuzzy Numbers

Chapter 1

Introduction

This chapter sets out to provide background and the motivation behind the thesis research with the main focus on Supply Chain Management (SCM) aspects of the small-series fashion industry. Building upon the background and the key concepts of small-series fashion SCM, the research problem, purpose of the research, and contributions are discussed.

1.1 Small-series fashion supply chain

The fashion industry is one of the most prominent industries that dominate the world consumer market. Broadly, fashion industry refers to the key operations starting from raw material manufacturing (fibers, yarn, fabrics, leather, fur, etc.), to the design and production of fashion products (garments, luxury items, etc.), sales and promotions, and finally to the delivery of these fashion products to the end-consumers. Due to the fast-paced transformations that fashion industry is undergoing owing to the technological advancements, shifts in consumer shopping behaviour, and regulatory recommendations for the sustainable production practices, there is emerging a new concept, known as small-series or make-to-order fashion that refers to the production of personalized fashion products in small-series characterized by long life cycle and high cost, which differs from the traditional fashion business model.

In recent years, there are increasing numbers of online fashion retailers, who offer customers a chance to customize their own products while sitting at home with just an internet at their fingertips, which is possible due to the advanced e-commerce web platforms powered by new

technologies such as Virtual-try-on, 3D configurators, body scanners, and so on. Moreover, fashion is taking on a new paradigm where consumers are much more concerned about the ecological aspects of their fashion consumption, which is contributing to the growth of small-series fashion as a sustainable option (Fletcher, 2010). While market trends are shifting towards small-series fashion, fashion retailers find it difficult and challenging to fulfil the customer demands in order to survive in the fierce market competition. This new trend, therefore, triggers the strategic operations and planning aspects of the fashion industry.

Small-series fashion is also being considered to be the response to the traditional fast-fashion business model wherein companies produce large quantities of cheap and trendy products and drive consumers towards unsustainable consumption behaviours. Moreover, small-series fashion seems to fit in the *Circular Economy Model* that aims to facilitate sustainable production cycle (Smith et al., 2017).

The fashion industry is evolving at faster rates, and the decision making related to its various business operations is increasingly becoming complex and challenging due to dynamically changing consumer preferences and market competitions. Fashion retailers' main aim is to run their business operations as efficiently and smoothly as possible for which they rely mostly on their decision models and valuable data collected from different sources (Giri, Jain, et al., 2019). The key to remain competitive and winner in the fierce market race, fashion retailers are changing various aspects of their business models, right from sourcing raw materials and manufacturing finished fashion products to the marketing and sales.

Small-series fashion, being the new avatar of the fashion business, necessitates the structural changes in retailer's business models, especially from the standpoint of their capabilities, flexibility and unique competencies, and such changes would, in turn, enable them to provide satisfactory services to their customers, thereby gaining their loyalty. Consequently, it leads to

the need to undergo rapid adaptations on the part of fashion retailers to serve the growing needs of customers and to tackle complexities arising due to the volatile market conditions.

Fashion retailers find it indispensable to tap into the holistic and real-time data of their customers, supply chain partners such as suppliers, manufacturers, designers, and logistic providers, etc. to be able to derive significant knowledge that is crucial for decision making in the fashion design, and manufacturing of high-quality fashion items, and thereby to stay ahead of the market competitors.

From the perspective of small-series fashion retailers, the tools for creating dynamic platforms for engaging customers and suppliers into design and manufacturing processes are highly important. Moreover, creating a long-lasting larger impact on customers' lives has become an integral part of their business operations. This, however, comes at the cost of huge investments in new tools and technology that serve both companies' and consumer goals.

In a typical traditional fashion supply chain management framework, fashion retailers and their stakeholders operate as individual independent entities pursuing their own distinct business goals, and in order to achieve these predefined goals, these competing entities form interconnected business networks among them based on their goals (Christopher et al., 2004). In this whole process, individual consumer preferences are not necessarily taken into account while transforming the business goals of the supply chain entities into the high business profit derived from the sale of the final form of finished fashion products via multiple stages of operations such as design, sourcing, production, marketing and sales. This process constitutes the so-called *push-supply chain system*, as shown in Figure 1.1, wherein fashion retailers push fashion products to the consumer market based on their suppliers' capabilities related to design, quality and style features of the products (Gérard P. Cachon, 2004).



Figure 1.1: Traditional fashion push supply chain system

Fashion retailers initiate their supply chain operations with the partnership with all the supply chain agents well before the selling season starts, and the risks, however, associated with the business operations such as inventory, logistic and the product delivery fall largely on the retailers themselves owing to the individualistic nature of their supply chain network relationships with other agents (Brun et al., 2008). The time span required for pushing the fashion products to the market range from as long as ten months to as short as three weeks (Bruce et al., 2004). It means that the decisions related to determining inventory levels for the raw material such as yarn and fabric, and the quantity of the fashion items to be merchandised in the typical brick-and-mortar retail outlets are mainly based on the forecasts of the future market demand and sales (Castelli & Brun, 2010). Moreover, the decisions related to supplier selection for building supply chain network relationships do not take into account the consumer specifications related to the fashion products they purchase from the physical retail shops. Therefore, the partnership of fashion retailers with their suppliers is mainly based on the strategic business goals of the retailers and the risk-sharing is not permissible unless the buy-back agreements are signed beforehand in case of low sales (X. Wang & Liu, 2007).

As illustrated in Figure 1.2, major supply chain operations initiated by fashion retailers and garment manufacturers in a traditional fashion business include purchasing raw materials such as fabric in bulk after finalizing the broadly categorized product designs. Subsequently, the orders for finished fashion products are sent before six to nine months prior to the selling season. The decisions related to the buying quantity of the products are taken by retailers on the basis of a variety of factors such as sales in the previous season, market trends, marketing campaigns such as fashion shows and media publications, and market research, etc. (Hilletoft & Hilmola, 2008).

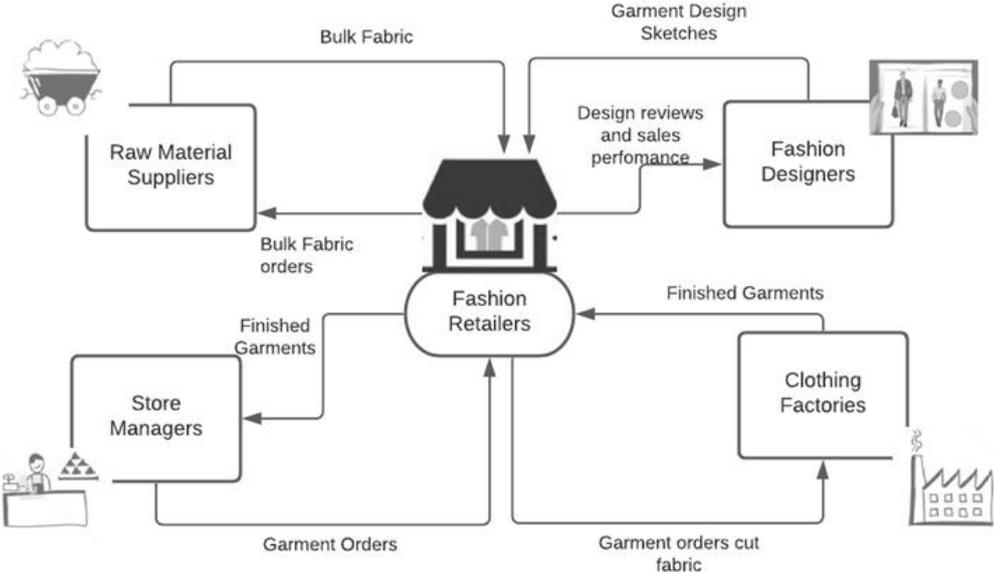


Figure 1.2: Key supply chain operations in a typical fashion industry

Small-series fashion, on the other hand, is the emerging trend in the fashion industry, and it adds to the complexity of supply chain management more than the traditional fashion supply chain. Given the deep level of customization preferred by the customers, retailers need to transform their SCM practices and need to emphasize more on building reliable, efficient, and

long-lasting SC system. This, however, is a daunting task from the perspective of a varying degree of challenges they face during building collaborations with their partners such as designers, suppliers as well as customers. With the growing need to overhaul their traditional production planning and procurement strategies, there are plenty of avenues for further improvements in their existing SCM systems.

Small-series fashion supply chain leverages on newly emerged technologies such as IoT (Internet of Things), AI (Artificial Intelligence), Big Data analytics that allows retailers to derive significant knowledge about their customers' choices as they matter the most for further planning and designing agile and quick response SCM strategies (Banica & Hagi, 2016). Rapid digital transformation of fashion industry towards e-commerce business models and the new advanced cloud-based computing services have enabled fashion retailers to track the information of their customers, designers and suppliers in a real-time, thus giving a new digital structure to their supply chain, as illustrated in Figure 1.2. From Figure 1.2, it can be considered that the small-series fashion supply chain is a complex interlinked system of various components in the form of suppliers providing different services.

The new *avatar* of small-series fashion supply chain, as shown in Figure 1.3, demand new SCM strategies that include changes in the supplier selection and collaboration strategies as the customers play a key role in the way retailers select their suppliers rather than it being driven by retailers' specific goals as it has long been the case in the traditional fashion supply chain. Moreover, efficient customer order processing requires new solutions in order to improve the performance of the SCM system as the customer choices for personalized products demand efficiency, flexibility and responsiveness in the SCM system.

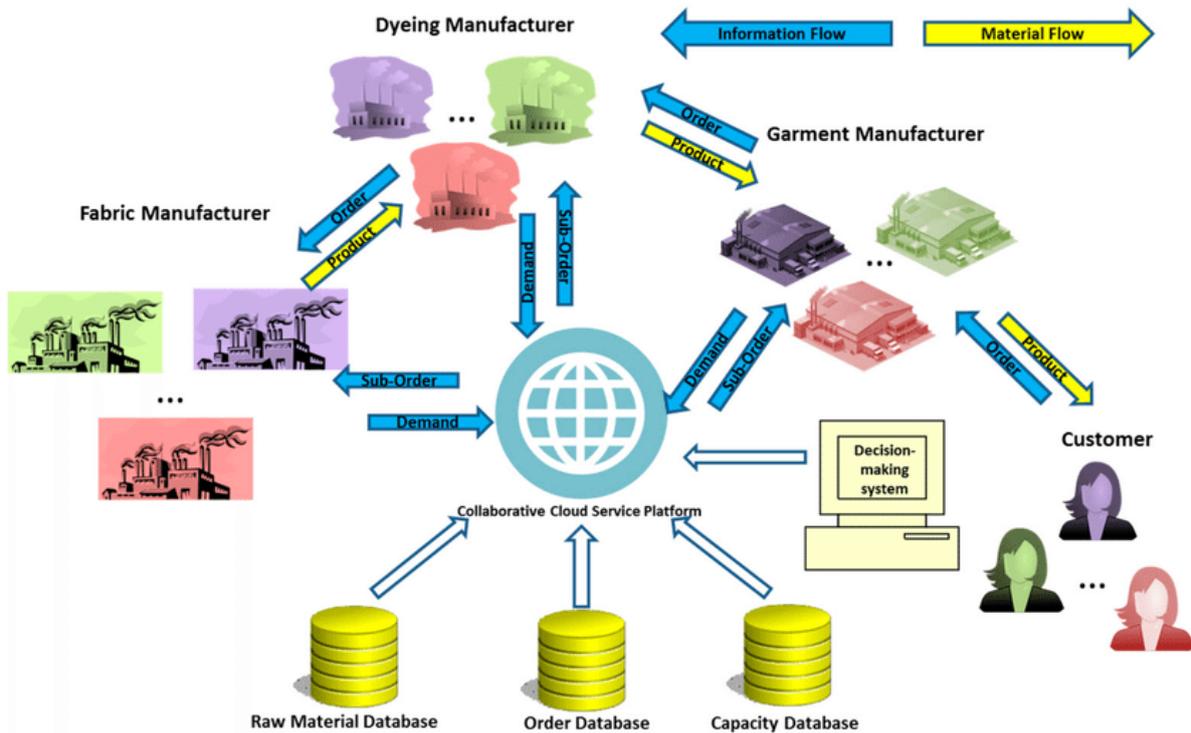


Figure 1.3: Collaborative small-series fashion supply chain platform (Ma et al., 2018)

There exists a vast literature on traditional fashion supply chain management problems; however, the same in the context of small-series fashion have not been adequately investigated. There is a significant dearth of studies that address supply chain problems in the small-series fashion industry. As the production planning and supply chain coordination problems are investigated mainly in (T.-M. Choi, 2018); (Wong & Leung, 2006); (Ma et al., 2017); and (de Leeuw & Fransoo, 2009), various solutions for operational problems are developed such as modelling retailers' risk behaviour while making SCM decisions; optimal production of carton boxes as per the varying size of products; sustainability through information sharing via advanced technology such as cloud database services; and optimal decision making based on enhanced collaboration within the SC network. These solutions are based on mathematical, optimization and simulation models, and do not capture other crucial aspects of small-series fashion SCM.

The small-series fashion supply chain warrants strategic efforts and responsive system that can enable customer order processing followed by SC decision making in a real-time. The first and foremost goal of small-series fashion business is to have a pool of highly trustworthy suppliers in its supply chain that ensures the business growth and more importantly, customer satisfaction and loyalty. The ability of small-series fashion retailers to facilitate sourcing, manufacturing and delivery of the customized small-series fashion items based on real-time customer demands is integral to the success of small-series fashion industry.

The main focus of this thesis is, thus, explicitly on the small-series fashion supply chain, which offers great opportunities to explore the potential of the availability of customer order data and the scientific methods to solve the challenging problems such as the selection of best-matching suppliers for the customer orders of customized products; order allocation; and strategic decision making for partnership based on various criteria. Furthermore, there is a great potential to improve the responsiveness of SC from the point of view of production and delivery, as the customers expect low lead times, and therefore, the aspect of effective order processing is explored in this thesis. Moreover, by exploring the aforementioned opportunities, efficient decision support system could be developed based on new methods in order to build and configure a reliable SCM system for the small-series fashion industry.

1.2 Problem statement

The research problems that are focused in this thesis are the part of the FBD_BModel Project¹ funded by the European Union under the Horizon 2020 programme. The overarching objective of the FBD_BModel Project is to develop knowledge-based business models to provide the small-series fashion products to the customers in real-time through localized supply chain.

¹ <https://www.fbd-bmodel.eu/>

The supplier selection problem in the small-series fashion industry is a two-stage process. As illustrated in Figure 1.4, the first stage focuses on the selection of raw material suppliers who, either directly or via retailer, provide fibers, yarns, dyes, fabric, etc. to the garment manufacturers. The small-series fashion retailer needs to decide as to who are the most suitable raw material suppliers among the candidate suppliers with respect to the business goals and strategies. However, the frequency of raw material supplier selection is very low, and it changes only when the new raw material suppliers offer to provide new raw materials with different attributes than the existing suppliers, and therefore, the decisions related to the raw material supplier selection are static. Moreover, the decision factors or the criteria based on which the raw material suppliers are selected are aligned with retailer's goals and strategies that may not evolve rapidly. Depending on the frequency of the arrival of new candidate raw material suppliers, retailers need to solve this decision problem effectively. Therefore, the process of raw material supplier selection can be considered as the *Push* system, in which the specializations of the raw material suppliers with respect to the fabric varieties are taken into account for providing different customization choices to the customers via e-commerce platform.

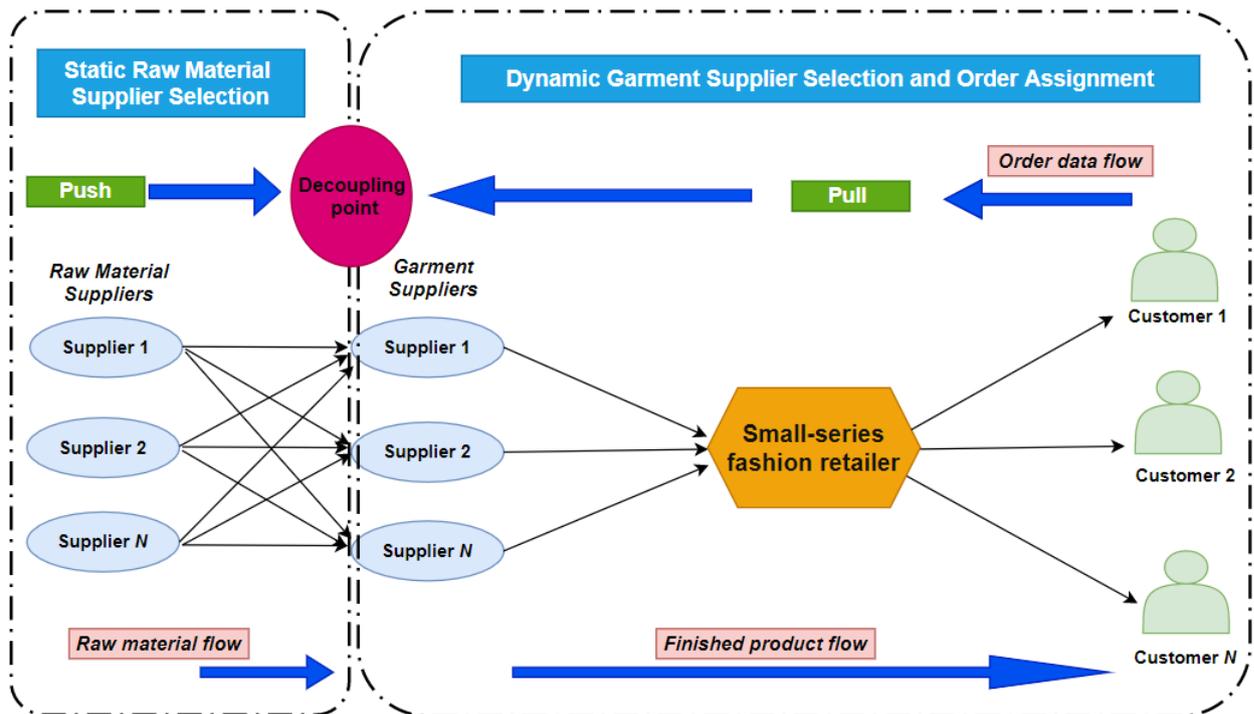


Figure 1.4: The schema of the small-series fashion supply chain

On the other hand, the second stage of the small-series fashion supply chain focuses on the selection of garment suppliers, who provide finished products to the end customers based on their customization preferences. This process is a dynamic one in which customer orders are pushed by the customers via e-commerce platforms and it triggers the garment supplier selection and customer order assignment process in real-time. The prerequisite condition for the garment suppliers is that they must maintain the inventory levels required for the fulfilment of dynamically arriving customer orders. This implies that the retailer or garment suppliers should have a mechanism to select raw material suppliers based on their strategic partnership and criteria matching. The frequency of order assignment to the best garment supplier is high and it must be done either daily or weekly depending on the number of orders. So, the dynamically arriving customer orders drive order assignment to the best garment

suppliers unlike raw material supplier selection process, which is static and not directly driven by the customer orders.

In the context of the small-series fashion SCM, the efficient sourcing decisions for the raw material and the finished products are critical for the growth and success of the small-series fashion industry. It is indispensable for the small-series fashion industry to adapt to the dynamically changing customer choices and to develop an efficient decision making mechanism to better serve their customers in terms of improved and quick availability of the high quality customized products. There is growing a need for the automated decision mechanism that can ensure the optimized performance of the supply chain within the small-series fashion industry. These aspects are the main focus of this thesis given their importance and relevance to the value creation in the modern small-series fashion supply chains.

The research problems investigated in this thesis are described as follows:

- Selection of best suppliers for providing raw materials and finished small-series fashion products to the customers

The success of small-series fashion industry heavily depends on the suppliers that constitute its supply chain, and their performance in terms of providing high quality customized products and services in a real-time is integral to its business growth. Failing to identify such suppliers, who need to be the best match for particular customer orders, could lead to the loss of market share and heavy revenue losses due to customer dissatisfaction. Therefore, highly efficient supplier selection approach should be developed, and it should be customer-oriented. Fashion retailers now have more opportunities to learn about their customers' personalized preferences and to align them with the supplier selection process. Moreover, how supplier selection can be achieved in a small-series fashion industry that is driven by e-commerce and digitalization and thus by the influx of customer order data is a potential area for research as it

has not been given attention in the small-series fashion SCM context. How the factors that are driving raw material supplier selection decisions have evolved due to the small-series fashion trend is a topic worthwhile to be investigated. Many conflicting criteria are to be considered for selecting raw material suppliers, and it makes the supplier selection problem more challenging and complex to solve. Another research opportunity arises from the growing popularity of AI techniques that are becoming efficient in solving a wide range of decision problems across many industries. In this thesis, the application of AI in solving garment supplier selection problem using customer order data is explored as a promising area for research.

- Dynamic customer order processing

Another aspect of small-series fashion supply chain is its operational decision problem that is real-time demand-driven oriented. In an interconnected small-series fashion supply chain system, customer orders are stored in the central databases of the retailers, who also can access the data of their suppliers entailing the attributes related to their competencies, capability, production-related factors, and so on. As small-series fashion promises to fulfil customers' objectives that finally align with retailers goals, allocating customer orders to the best supplier in a real-time so that these objectives are achieved is a difficult task. This thesis focuses on automating customer order allocation to the best suppliers while keeping into account these objectives.

Customer demands for small-series fashion products are cost and lead time-sensitive beside quality factor, and they prioritize their satisfaction that they seek from the customized fashion products. Customers generate complex data related to their expectations during their online shopping, and making order allocation based on this data is of great significance from the research point of view. Therefore, this thesis aims to explore the opportunity to develop a

model for assigning customer orders to the best suppliers. This model could be relevant for small-series fashion companies as well as for the researchers in academia and in the industry focusing on supply chain aspects.

Based on the literature review, it is identified that order planning constitutes the important decision area in small-series production systems beside production planning and SC coordination; however, there is a dearth of researches on fulfilment of dynamically arriving customer orders in specified time windows. This offers an interesting opportunity to explore dynamic order sequencing problem in a small-series fashion framework. Modelling customer data for computing lead time and the profit of the retailer based on customer data as an input is an important decision problem that is explored in this thesis.

1.3 Purpose

It is indispensable for the small-series fashion industry to select the best suppliers in order to improve the efficiency of their SC co-ordination strategy. Rapidly growing preferences for customized fashion items in the market is shifting fashion industry towards focusing on fulfilling individual customer demands for a variety of body sizes, style, colours, textures, knitting and stitching patterns, etc.

It has become a great challenge for the small-series fashion companies to fulfil the customer demands, and therefore substantial overhaul in the traditional ways in which they selected their suppliers and promised orders to their customers is necessary. Mass fashion business model is not sustainable, and the SCM practices are no longer suitable for managing its new version, i.e. small-series fashion SCM decision problems.

In this broad context, the main purpose of this thesis is to solve three main Supply chain management problems; using the retailers' supplier and customer data. In this context, the overarching research questions that this thesis aims to address are formulated as follows,

***RQ 1:** How the raw material suppliers for small-series fashion production can be selected in supply chains?*

***RQ 2:** How the best suitable garment suppliers for the fulfilment of newly arriving customer orders of small-series fashion products can be predicted in a real-time?*

***RQ 3:** How the customer orders of small-series fashion products can be effectively sequenced and assigned to the best garment suppliers in a way that it meets the objectives of the retailers and customers?*

The research questions formulated above focuses on operational decision problems in the small-series fashion supply chains, and they aim to address the challenges faced by small-series fashion industry due to the recent transformations. These three main research questions are highly relevant from the perspective of decision making in the small-series fashion industry. These three research questions together constitute the overall research framework of this thesis, as depicted in Figure 1.5.

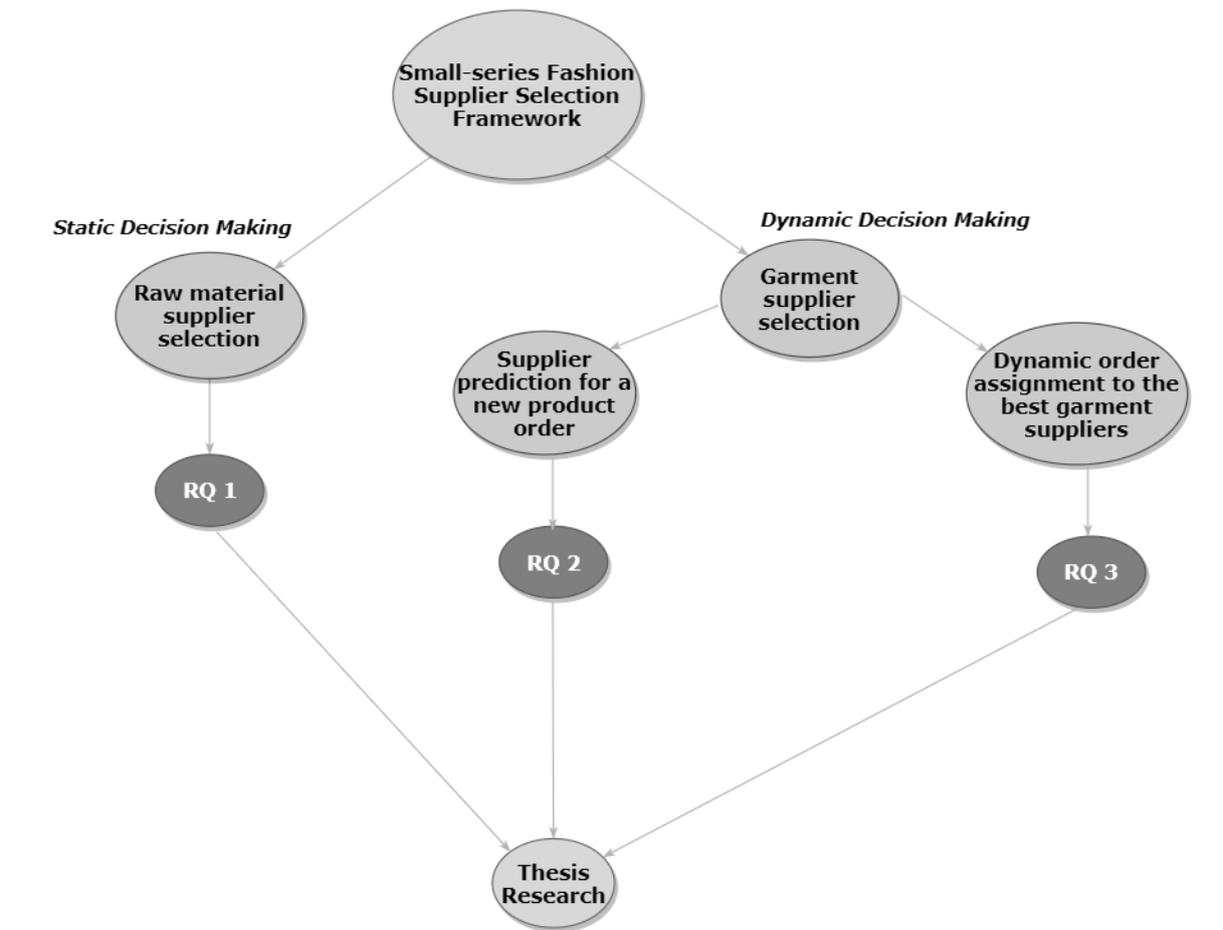


Figure 1.5: Thesis research framework

1.4 Contribution

Based on the premise outlined in this thesis using the systematic literature review, the experimental part of this thesis, presented in Chapters 4, 5 and 6 respectively, highlight the significant contributions to the research field of supply chain management and to the managerial decision making in the small-series fashion industry.

The main issues related to small-series fashion supply chain and production management decision problems are investigated in this thesis through experimental research approach, and it has a real practical significance for both the small-series fashion industry and academic research field. The three research questions formulated based on the identified gaps in the

literature are highly relevant to today's complex decision-making mechanism in the small-series fashion industry, and they constitute valuable impact on the way in which key operational decision problems are solved in real business scenarios.

Developing the mechanism for selecting suitable suppliers for the customized small-series fashion products is crucial for the fashion retailers, and it can enable them to devise an optimal approach in their sourcing decision making and effective SC network relationships with their suppliers. Small-series fashion industry is growing rapidly due to the ever-evolving edge of advanced technologies such as Database management tools, cloud computing, AI, social media, etc. The research questions investigated in this thesis make substantial contributions to the fashion industry in terms of enabling efficient approach for solving key operational SCM decision problems.

From a methodological point of view, this thesis extends the applications of scientific methods utilized for investigating the defined research questions, and they constitute the novel and innovative approach for solving real industrial decision problems in small-series fashion framework. Fashion retailers could apply these methods for their business decisions and utilize the insights developed in this thesis for examining various case studies related to products and business strategies.

As regards scientific contributions of this thesis, I explored the possibility of involving supply chain decision-makers from the small-series fashion industry and the data related to their evaluation of various decision problems are generated as valuable inputs for the models that are proposed for solving supplier selection, prediction of the best suitable supplier and the dynamic order allocation problems. Moreover, industrial data used for predicting best suitable supplier for the dynamically arriving new customer orders is crucial for extending similar approach for solving the decision problems in different products and industry scenarios.

The experimental work conducted in this thesis is unique in the sense that novel research problems are identified and explored based on their relevance and real business requirements of the small-series fashion industry. In this way, this thesis presents an experimental approach that can be extended to other industries that specialize in small-series production.

1.5 Thesis outline

The thesis is comprised of a number of chapters. In Chapter 1, the general introduction to the thesis topic, i.e. small-series fashion supply chain management, is presented. The purpose of the thesis research is outlined further along with the background of the thesis topic.

Chapter 2 is devoted to investigating the existing status of the researches on a chosen thesis topic through systematic literature review, and it forms the main premise of the research work conducted as part of this thesis. The literature review presented in this chapter focuses on identifying key research opportunities in small-series fashion supply chain management.

Following the literature review, background of scientific methodology that is used for conducting the research in the thesis is described briefly in Chapter 3. The given methodology is selected in line with the nature of the research questions formulated in this thesis.

In Chapter 4, the first research question (RQ1) is elaborated at length, and experimental implementation of the chosen methods for static fashion supplier selection is described along with the obtained results.

A dynamic supplier prediction problem as a second research question (RQ2) is detailed in Chapter 5, and the implementation and the results of applied machine learning methods are discussed.

Chapter 6 presents the second aspect of dynamic decision making as part of fashion garment supplier selection for the customer order fulfilment in real-time. The applied Genetic

algorithm (GA) and GA-TOPSIS models are used to address the third research question (RQ3), i.e. to dynamically assign customer orders to the best suitable garment suppliers.

Finally, the conclusion of the thesis is discussed in Chapter 7, and it further provides the limitations, and future scope of the research carried out in this thesis.

Chapter 2

Literature review

In this chapter, a broad overview of how the fashion industry has evolved over the last several years is presented. A comprehensive literature review on small-series (make-to-order) SCM principles serves as the solid foundation for the research goals pursued in this thesis. The key elements that constitute the small-series fashion SCM system as a whole are identified and discussed in this literature review. In the end, it provides the introductory background to the current SCM problems in the small-series fashion industry, their significance, new challenges and opportunities and scope for the future research projects.

2.1 Evolution of the fashion industry: from fast-fashion to slow-fashion

The fashion industry, in general, has often been ascribed by two key aspects: *Fast-fashion* and *Slow-fashion*. The production of fashion products operates on two levels: Mass scale fashion production (*mass production*), and Small scale fashion production (*small-series fashion*).

In a fast-fashion paradigm, the fashion products are produced in a large number quantity and are characterized by the low selling cost, low production cost, and fast stock turnaround (Joy et al., 2012). Fast fashion is based on the mass production strategy, wherein the major focus is given on the fulfilment of broadly categorized customer demands by undertaking mass-scale production. Fast fashion has long remained one of the prominent SCM strategies in the fashion industry (Tsan-Ming Choi et al., 2010). Fast-fashion enables fashion retailers or manufacturers to introduce new varieties of fashion products to the consumer market within a very short time span and thereby to quickly create new fashion trends (Fernie et al., 2010). With the main goal of speedily selling latest varieties of fashion items to the consumers, fast-

fashion adopts quick-response SCM strategy, which includes high-speed product delivery and a high degree of flexibility (Tokatli, 2008). Fast-fashion products are characterized by their short life cycle, low prices and rapid penetration to the consumer market.

As fast-fashion companies need to produce fashion products in huge quantities to meet the growing consumer demands, agile and highly effective supply chain management strategies play a crucial role in the industry's business growth. High-speed replenishments, efficient inventory management, accurate demands forecasting, low lead times are the important SCM strategies that fast-fashion retail companies must adopt to fare well in the fierce market competitions and to maximize profitability. Some of the most successful fashion retail brands that adopted fast-fashion business models are Zara, Forever 21, H&M, etc.

One of the main SCM strategies for the fast-fashion industry is intelligent forecasting of customer demands and product sales. (Brahmadeep & Thomassey, 2016) proposed two-stage intelligent demand forecasting system based on AI models that highlight the significance of advanced forecasting system to manage fast-fashion supply chains. Demand forecast based production planning is the key feature of fast-fashion SCM. Accurate forecast of the consumer demand is critical for the efficient inventory planning in fast-fashion industry. (T. M. Choi & Ren, 2016) proposed an integrated inventory model based on fast-fashion demand forecasting. (Giri, Thomassey, et al., 2019) proposed another interesting sales forecast system based on fuzzy logic using historical sales and social media data. Since fast fashion business relies on efficient inventory management for which accurate forecasting of consumer demands is necessary, efficient and intelligent demand forecasting system is the most important component of fashion SCM.

While fast-fashion has tremendously dominated the luxury and apparel market in the last decade with the help of effective SCM strategies, it has caused many serious issues that

attracted the flak from the regulators, academic researchers, civil societies, and environmentally conscious consumers. Fast-fashion has shifted consumer purchasing behaviour towards unsustainable fashion consumption, and while primarily focusing on increasing profit margins by fulfilling unsustainable consumer demands, fast-fashion companies adopted unsustainable manufacturing practices that lead to environmental hazards (Mcneill & Moore, 2015).

Fashion products manufactured in fast-fashion industries usually have a short life cycle, sometimes as few as three or four months, owing to which most of them are disposed away from the consumers' closets and end up in rivers, oceans, and land-fills causing huge danger to the ecosystem (Runfola & Guercini, 2013). To keep up with the growing consumer demands for cheap and trendy fashion items, fast-fashion companies have long indulged in violating the safety standards in their production plants, exhibited no regard for the wellbeing of the labour force, and shied away from their responsibilities towards the environmental mottos of the countries in which they mostly operate their production activities.

For these reasons, the fast-fashion industry has exhibited reckless and irresponsible traits such as poor compliance with the environmental standards in their manufacturing practices, violation of labour laws, compromised product quality, poor waste management, and dubious ways to mislead the regulators to escape their punitive radar.

In the last decade, there has been a growing global concern for sustainable development and more social and sustainable responsibilities (Waddock, 2008). It has also been accompanied by the strong criticism of fast fashion business models, which led to growing ethical pressure on fast fashion companies to adopt responsible attitudes towards social and ecological aspects of their business models. Intensified public criticism over unethical fashion manufacturing practices helped to spread more awareness among consumers about the negative impacts of

the fast fashion industry on the ecological as well as social aspects of the world. Consequently, it led to the emergence of slow fashion, a new form of fashion business where fashion products are characterized by the relatively long life cycle, reduced production quantity, and more importantly, sustainable manufacturing and SCM practices. Moreover, this emergence fostered the rise of new consumer philosophy, which is centred on conscious and ethical consumption (McNeill & Snowden, 2019). The more comprehensive description of slow fashion is given by (Jung & Jin, 2014) as follows,

“Slow fashion aims at designing, producing, consuming and living better by slowing down the fashion cycle, moving from quantity- to quality-based. Slow fashion is not just the opposite of fast fashion, but more sustainable and ethical ways of being fashionable. The concept of slow fashion borrows from the slow food movement, which links pleasure and food with awareness and responsibility.”

To establish the slow fashion trend amid the dominance of fast fashion market, a new form of the fashion trend has emerged in recent years, which is known as small-series fashion that allows a high degree of customization of the fashion products, and provides a high-quality product to the environmentally and socially conscious consumers. Small-series fashion thus has been considered to be conducive to the development of slow fashion trend in the fashion industry, which in turn contributes to achieving sustainable sourcing, production and distribution of the fashion products (Tsan-Ming Choi & Shen, 2016). Unlike fast-fashion, small-series, or make-to-order fashion involves a focus on high standard customized features of the garments matching with the customers' expectations, which usually takes longer production times, and thus lead times. Moreover, small-series fashion items are manufactured in a way that they can have long life cycle than fast-fashion items, and if produced in a sustainable manner, it could lead to the fulfilment of sustainable fashion manufacturing goals and thereby it could bolster slow fashion trend in the fashion industry. Small-series fashion

aims to offer a broad range of customized fabric, design and style features of fashion items to its customers (Jung & Jin, 2014). In this way, small-series fashion can pave the way for sustainable movement in the fashion industry.

Small-series fashion items are usually produced in small batches as the market demand for highly customized, high quality and costly fashion items is still relatively lower, and therefore, it can facilitate conscious sourcing of raw materials, reduced consumption of synthetic raw materials, and better waste management practices.

2.2 Key factors shaping the small-series fashion industry

2.2.1 Digitization

The fashion industry, among the many prominent industry sectors, is highly influenced by Information and Communication Technologies (ICTs). The rapid adoption of digital tools and technologies for various operational level tasks such as design, garment manufacturing, sales and marketing, and customer relationship management (CRM) is increasingly prevalent in the fashion industry. Digital technology platforms are gaining popularity in a range of operations such as fashion design, and it is transforming the traditional ways of fashion design (Tu & Wang, 2018). The growing popularity and transformative power of digital technology have fostered the rapid growth of e-commerce fashion retail platforms that are primarily aimed at providing customers with diverse in-store experiences in virtual online platforms.

The fashion industry is shifting to e-commerce business models that enable customers to participate online in the design and manufacturing of their chosen fashion products with a high degree of personalization. Many small-series fashion retail companies are developing advanced, user-friendly user interfaces to allow their customers to have a virtual try-on, product image interactivity, and access to every minute product information, and enriched product browsing experiences on their highly interactive websites (Plotkina & Saurel, 2019).

With the strong combination of highly interactive image technology and web-based technology, e-commerce fashion retail brands are able to enhance customer evaluation and try-on experiences of fashion items with the use of 3D animated videos, ultra-zoom functionality, and simulation of their purchase activities.

The digital revolution in the fashion industry has given rise to small-series fashion as a new frontier in the fashion industry, and it is enhancing customer shopping experiences and their commitment to sustainable fashion consumption. Unlike brick-and-mortar fashion stores, digital small-series fashion platforms provide a wide range of product varieties and increased personalized shopping satisfaction to the customers living in different locations of the world. Social media has also contributed significantly to the growth of e-shopping fashion retail shops where customers crave for highly personalized fashion garments that best reflect their individual traits and resonate with their ideal social media avatars (Nash, 2019). Consequently, customers are flocking to e-commerce fashion platforms more than ever as they enhance their shopping experiences and provide personalized small-series fashion products.

2.2.2 AI & Big data

AI and Big Data have revolutionized various businesses across the world in an unprecedented way because of its power of automating difficult tasks with higher accuracies and high-speed computation. The fashion industry is surely not beyond this transformation. AI and Big data are contributing to solve a plethora of decision problems across the fashion supply chain stages right from the design, production, logistics, and sales & marketing to the retailing and distribution. AI has found a multitude of applications in the fashion industry, especially in the clothing design and manufacturing processes (Dennis, 2019).

In particular, AI and Big Data Analytics help automate small-series fashion processes such as virtual and graphic garment design simulation-based on customer data, modelling consumer fitting styles and recommendation of a huge range of personalized services and fashion preferences based on consumers' search queries and their interaction history with e-shopping web platforms (H. Wang & Rasheed, n.d.). Since consumers spend a considerable amount of their time on social media, AI helps fashion retailers to tap into customers online footprints on social media, which further helps them to detect new customer trends specific to their fashion choices (Luce, 2018).

AI has paved the way for the emergence of direct-to-customer business models in small-series fashion, which enabled retailers to increase their profit margins as they can save on operating and warehouse costs. Moreover, advanced database and cloud computing technologies enable the direct access to customer and supply chain data to all the agents involved in the small-series supply chains, which further helps boost the operational and overall efficiency of the fashion business (Luce, 2018). AI has also been found to have improved the efficiency and responsiveness across all the stages of the fashion supply chain, and it is increasingly becoming critical to the success of e-commerce small-series fashion retail business (Liang et al., 2020). Make-to-order garment manufacturing can be facilitated in small-series fashion and can be widely promoted by deploying AI models into online shopping platforms as they are highly efficient in extracting personal consumer preferences and allowing them to design their own fashion products virtually. E-commerce platforms of the small-series fashion retailers produce a huge amount of data from customers as well as from their suppliers, which creates big challenges for them to derive insights from it and make decisions based on them. AI performs advanced predictive analytics on this data and help fashion retailers make smart decisions related to design, manufacturing and sales (Thomassey & Zeng, 2018). Moreover, AI has been increasingly used to improve customer relations and their grievances by AI-based

voice assistants and chat-bots (Liang et al., 2020). The fashion industry, being one of the most polluting industries, is seeing important benefits of AI in terms of reducing inventory and creating sustainable solutions in small-series fashion manufacturing.

2.2.3 Industry 4.0

Industries are undergoing transitions and shifting towards digital technology-driven new manufacturing and distribution paradigms. This trend of the industrial revolution is called as Industry 4.0. Industry 4.0 enables a central interconnected system of all the participating agents and stakeholders and allows them to share their data with each other in real-time (Paola Bertola & Teunissen, 2018). Small-series supply chain is a form of such a system where all the agents such as retailers, manufacturers, suppliers, designers, and even customers exchange their data with the central information system powered by digital networks and interactive platforms. This new systemic approach enables small-series fashion business to solve a variety of complex operations related decision and supply chain problems in an efficient manner based on advanced data analytics operations on the huge data of all the agents in the system. Industry 4.0 provides the fashion industry with sustainable and efficient production and distribution models (P Bertola & COLOMBI, 2014).

Industry 4.0 paradigm has made it possible for all the agents in small-series fashion supply chain to participate virtually in the design, manufacturing and distribution of customized fashion products best aligned with customer preferences, which is why Industry 4.0 is creating greater implications for the fashion industry. With the embracing of Industry 4.0 paradigm, small-series fashion is entering into a new age and becoming a smart system capable of producing smart fashion products using smart digital networks and smart production and SCM systems. Moreover, fashion Industry 4.0 is capable of exploiting social media insights of the customers and their dynamically changing preferences in order to enhance

customization features and the design parameters of the fashion products (Hermann et al., 2016).

2.2.4 Micro-factory framework

Micro-factory is a newly emerging concept in the manufacturing systems, which is broadly defined as a small-sized manufacturing system designed to produce products with the less consumption of resources and energy, and space (Siltala et al., 2010). Micro-factory manufacturing system facilitates sustainable and adaptive manufacturing practices as the manufacturing processes are driven by the real-time demand of customized products, thus requiring only a small batch for production at a time, which in turn utilizes the less amount of raw materials and yet capable of producing high quality customized products (Järvenpää et al., 2015).

Since the micro-factory manufacturing system is adaptive and responsive to the high degree of fluctuations in the consumer demands for customized products, the flow of customer orders and in the resource utilization for the production, it is crucial for enabling small-series fashion production, which faces the same level of dynamics in its production processes. Rapid technological advancements play a crucial role in enabling micro-factories to develop and align these technological tools into their manufacturing systems to be able to stay ahead of their competitors by adopting sustainable and highly agile manufacturing processes (Bicocchi et al., 2019). As the micro-factory paradigm emphasizes on the production downsizing (Pérez et al., 2013), the small-series fashion industry can lead towards sustainable manufacturing by embedding into its production processes the very principles of micro-factory manufacturing concepts that are suitable and indispensable for the small-series industry to survive the fierce market competition and enhance its business growth.

2.3 SCM in small-series fashion

Given the rapid transformation of fashion industry driven by dynamic nature of customer choices and market trends and the adoption of advanced ICT and AI and Big Data technologies, solving SCM related decision problems is becoming increasingly complex and challenging. Robust and highly effective SCM is extremely crucial for the fashion industry to ensure profitability and the growth of its business, and to gain a competitive edge in the market as it mainly relies on how effectively its SCM system meets the challenges arising out of customer demands and how accurately it predicts and mitigates business risks (Banica & Hagi, 2016).

Small-series or make-to-order fashion products are personalized by the customers themselves in a real-time by feeding data of their own specific preferences via fashion retailers' online retail websites that are powered by ICT technologies such as CAD, 3D virtualization, body scanners, and product style configurators. Once this data is fed to the retailers' databases, SCM network coordination gets triggered in order to finally manufacture and deliver the customized products ordered by the customer. Small-series fashion business calls upon all the agents involved in the supply chain to design and build highly efficient SCM coordination strategies given the deep level of product customization and a high degree of product differentiation expected by the customers of small-series fashion products. This scenario also leads to formulating efficient design, manufacturing and delivery strategies.

There exists an extensive literature on SCM strategies in the traditional fashion industry. However, there is a significant dearth of literature on the study of SCM strategies for small-series fashion. It can be attributed to the fact that small-series fashion is an emerging fashion paradigm. It is of vital importance to investigate as to what are the major challenges that small-series fashion paradigm generates given the extent of personalization expected by the

customers from small-series fashion products and the required level of strategic responsiveness, coordination, and flexibility of all the agents in small-series supply chain, mainly designers, suppliers and retailers.

This section provides a summary of an extensive literature review on two aspects:

- a. SCM in make-to-order system in different industries other than the fashion industry
- b. SCM in small-series (make-to-order) specifically in the fashion industry context

2.3.1 SCM in small-series industries other than the fashion industry

A systematic literature review (SLR), adopted in studies such as (Keathley et al., n.d.) and (Sulistio & Rini, 2015), is conducted in order to collect existing literature on primary studies on supply chain management in small-series (make-to-order) industries other than the fashion industry. This approach is used to investigate the nature of SCM problems in different industries as it is crucial to comparatively analyze the SCM problems in fashion industry vis-a-vis other industries.

In order to retrieve peer-reviewed journal articles related to the thesis topic, the Scopus database is accessed as it is the largest abstract and citation database of peer-reviewed literature². The search strings used to retrieve the articles related to the thesis topic are constructed using the search terms as follows;

("supply chain management") AND ("for" OR "in") AND ("small-series" OR "make-to-order") AND ("production")

The database search generated 62 articles in total. No exclusion criteria are applied to filter the articles as it is intended to gather holistic and broad literature for a comprehensive review of the supply chain in small-series (make-to-order) productions. Three articles were found to

² <https://www.elsevier.com/solutions/scopus>

be redundant for the literature review as they were repeated as two different publications, and so are excluded, which finally resulted in 59 article papers.

Figures 2.1, 2.2 and 2.3 given below show the distribution of retrieved articles as per the year of publication; type of publication; and the subject areas respectively.

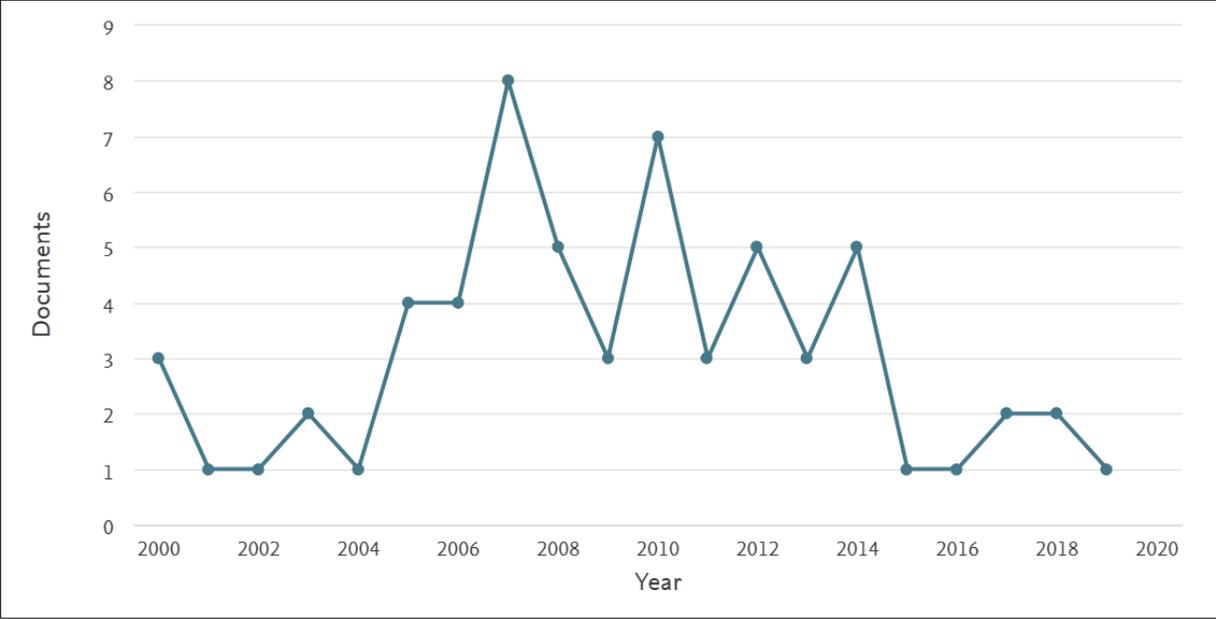


Figure 2.1: Scopus peer-reviewed papers by year of publication

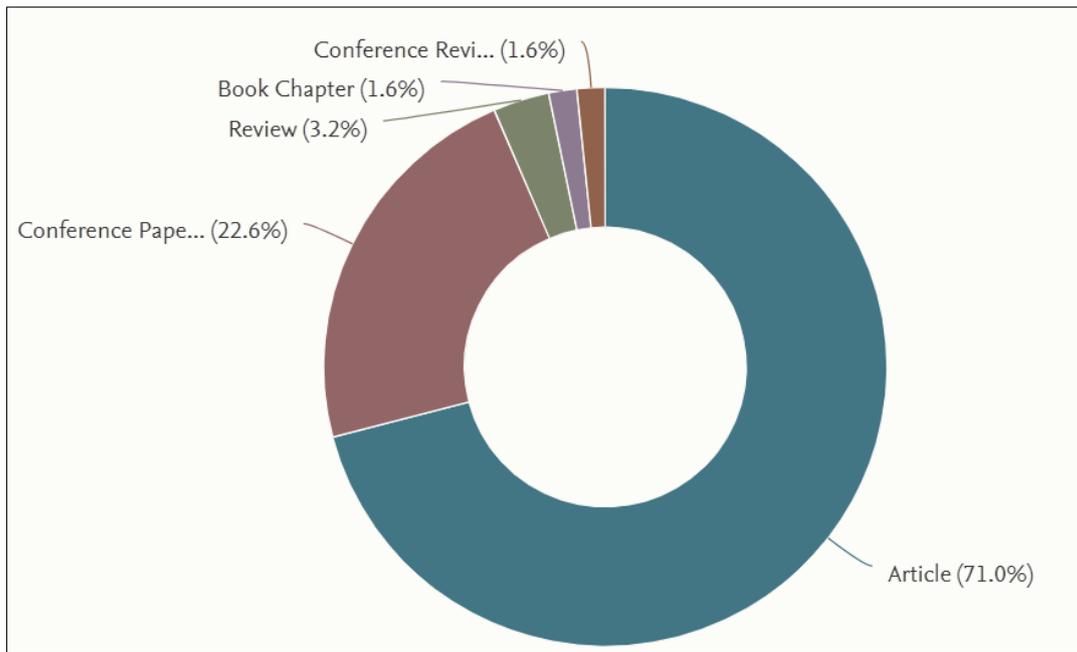


Figure 2.2: Scopus peer-reviewed papers by types

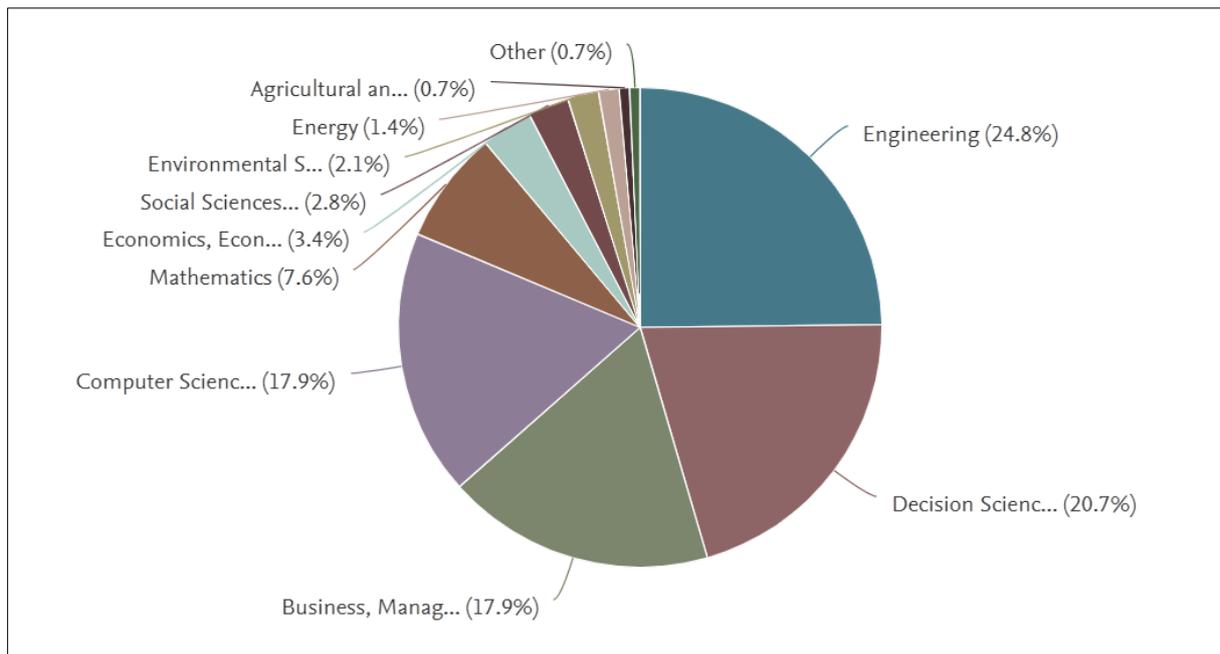


Figure 2.3: Scopus peer-reviewed papers by subject area

Supply chain management in small-series (make-to-order) context is a very broad research topic, owing to which the literature review presented in this section is, by structural literature

analysis, categorized into major structures as themes corresponding to main aspects of small-series SC. Five major themes, as shown in Figure 2.4, are identified from the literature study that provides a holistic view of various research trends in small-series SCM problems.

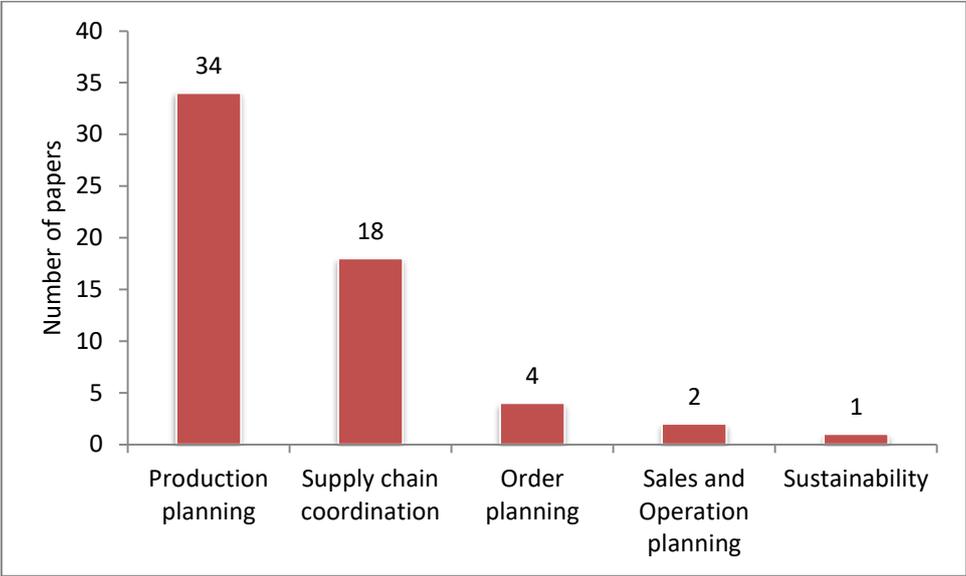


Figure 2.4: Scopus peer-reviewed papers’ distribution as per the themes

2.3.1.1 Production planning

Production planning is a key element of SCM in small-series industries. It entails various important tasks ranging from sourcing of raw materials and accessories to manufacturing assembly, resource and labour allocations, storage and inventory management, waste management and finally to the shipping of the final product (Vasnani et al., 2018). All these production planning related tasks are triggered when the customers place their orders to the retailer through various sales channels (Maheut et al., 2014). In a typical Make-to-order (MTO) production setting wherein customer specifications for customized products are taken into account beforehand for manufacturing those products, a retailer is considered to be at the centre of SC and its relationships with the agents in the upstream such as manufacturers and suppliers are of great importance from the point of view of manufacturing operations. Various

studies, for example, (Xiao et al., 2014); (Vasnani et al., 2018); and (Leng & Parlar, 2010) considered MTO product demand to be price and lead time-sensitive, and developed game-theoretic models to dynamically analyze the MTO SC involving various suppliers sensitive to order quantity as their decision variable. As the theme of MTO production planning has been the main focus of research in 34 articles falling under the theme, a wide range of production planning-related research problems are identified and addressed. As outlined in Table 2.1, the key production planning decision problems include reducing various production-related costs such as storage and transportation; coordinated decision making among suppliers processing MTO product orders; production scheduling with respect to various objectives; identifying priority product orders based on capacity and inventory levels; studying the performance of suppliers based on their interactions with other SC agents; reducing production cycle time; optimal procurement decision making; assembly planning and reducing tardy jobs; maximization of profit while selecting the orders for production; to identify priority orders for production keeping suppliers' various joint strategies into account; replenishment and inventory management decisions making; and joint production collaboration under shared information scenario.

The major research trend within production planning theme revolves around the joint collaboration under the data sharing scenario using conceptual modelling. However, data-driven approach for solving the aforementioned production planning decision problems is under-utilized.

Table 2.1: Summary of articles in production planning theme

Source	Research Problem	Method	Summary
(Vasnani et al., 2018)	decision b/w suppliers and manufacturer	game theory + fuzzy theory	The proposed models enable effective decision making when the demand is the price and lead time sensitive
(Alayet et al., 2018)	storage transportation	Optimization method	The proposed model is found to reduce the logistic cost of the forest SC
(Steinke & Fischer, 2016)	impact of network design on production and distribution	optimization method	Quantity of return product drives the decisions related to the utilization of return products
(Nedaei & Mahlooji, 2014)	multi-objective production scheduling	simulation technique	System performance is influenced by suppliers production flexibility and interactions with other external SCM factors
(Maheut et al., 2014)	order fulfilment	Literature review	Key decision factors are identified
(Viergutz & Knust, 2014)	demand management	heuristic algorithm	The proposed model finds a section of customers so that maximum demands are satisfied
(Rasti-Barzoki & Hejazi, 2013)	minimize the number of tardy jobs	Integer programming model + Heuristic Algorithm (HA) and a Branch and Bound (B&B) method	Through computational experiments, the optimization model is found efficient to reduce the tardy jobs

(Sharma, 2013)	reducing production cycle time	Literature review	Significant parameters, such as the production rate and cycle time, are identified in relation to other parameters such as demand, and production time cost.
(Rotondi et al., 2012)	effective partnership management	Literature review	Strategies for SC network configuration are discussed when producing products in small batches.
(H. Li & Womer, 2012)	optimizing sourcing and planning decisions	both mathematical programming and constraint programming	Optimal SC configuration decision solutions are developed.
(Tanrisever et al., 2012)	capacity management problem	multi-stage stochastic program and a sampling-based decomposition method	In the case of high demand variability, operational flexibility is beneficial when demand and capacity are well balanced.
(Xiao & Shi, 2012)	To develop lead time and price related production strategies	differential modelling	Dynamics of retailer's high market power is explored based on product differentiation.
(Jan Olhager, 2010)	to study the impact of customer order decoupling point on SCM and production strategies	conceptual model	A dual design approach for SCM and production planning system is found to be effective.

(Kristianto, 2010)	to study the effects of strategic decisions related to pricing and production size on profit and demand fluctuations	system dynamic study	Production size postponement is found to be effective for MTO.
(Su et al., 2010)	to study the effects of product delayed differentiation on a production planning decision	simulation technique	Delayed product differentiation results in short lead time and higher costs.
(Küttner, 2009)	to develop strategic production planning solutions for uncertain and variable MTO products	conceptual model	The proposed model considers different characteristics of product orders to develop production planning solutions.
(Lichun & Xiaoyi, 2008)	to determine the priority of buyer order	neural network model	The proposed model performs efficiently with short model training time while prioritizing the orders.
(Zhao et al., 2008)	to achieve joint replenishment in a single-manufacturer single-retailer supply chain	optimization methods	A solution for joint replenishment with the optimal cost is developed.
(Kaminsky & Kaya, 2008)	to explore the effects of partial information sharing on due dates assignments as part of scheduling	conceptual model	Production scheduling algorithm under the partial information sharing paradigm is developed.

(Sahin et al., 2008)	to study master production schedule (MRS) and advanced order commitment (AOC) in two-stage supply chains	conceptual model	Study of dynamic nature of scheduling and procurement systems is conducted for better coordination through MPS/AOC policy.
(Lan et al., 2007)	to optimize production planning for MTO SC	Lagrange Method	Optimal production planning solution based on the probabilistic market study is proposed.
(Gupta & Wang, 2007)	to dynamically select customer orders with profit maximization goal	heuristic algorithm	The effect of demand variability on the optimal profit is studied with respect to the capacity constraints of the suppliers.
(Wikner et al., 2007)	to explore the capacity and production planning problems arising from MTO SC	Literature review	Dynamics of mass customization system (MTS) has been deeply investigated, and the SCM challenges in regard to MTO SC are identified.
(J. Choi et al., 2007)	to optimize the production cost under different scenarios and further to develop optimal solutions for managing the MTO system	optimization model	The optimal solution for deciding the order processing time (order lead time) for MTO production system is developed.

(Dong et al., 2006)	to find the optimal solutions for managing synergic production processes based on negotiations	hybrid optimization methods	A model for managing SCs in synergic production systems is developed.
(Chan et al., 2005)	to coordinate manufacturing planning in a multi-product MTO system	conceptual model	Adaptive strategies for the effective co-ordinations between the SC agents in order to manage MTO SCs.
(Navas, 2005)	to discuss suppliers' strategies to increase profitability in the MTO system	literature review	Efficient information visibility across the whole MTO SC is effective in reducing costs and improving product sales.
(Stevenson et al., 2005)	to review classical production planning approaches	Literature review	The study highlights the key research opportunities for empirical studies in the area of MTO manufacturing system.
(Azevedo et al., 2004)	to coordinate production and order planning based on increased information visibility among SC agents	Multi-agent simulation method	The decision support based on multi-agent system is developed for effective SC coordination among the agents.
(J. Olhager, 2003)	to identify the right product manufacturing and delivery strategies	conceptual model	Various product manufacturing and delivery strategies for different scenarios have been proposed.

(He et al., 2002)	to manage inventory control with the proper information sharing among SC agents	dynamic programming	The study finds that the total inventory cost can be significantly reduced by proper information sharing in inventory control operations.
(Kolisch, 2000)	to assemble multi-product orders in the MTO system	mixed-integer programming	Optimization method based model is applied to coordinate fabrication and assembly under capacity constraints.
(Rupp & Ristic, 2000)	to design effective production and control planning strategies for MTO environments	conceptual model	Order due dates are modelled using the capacity models of the MTO companies, and the optimized solutions for global order allocation have been developed in a virtual setting.
(Azevedo & Sousa, 2000)	to solve the problem of producing customer orders in a distributed manufacturing and information sharing framework	simulation technique	The problem of planning an incoming customer order is addressed using simulation in a distributed (multi-site) and multi-stage production system.

2.3.1.2 Supply chain co-ordination

From the review of the selected corpus of literature, it is found that Supply chain coordination is the second most focused theme in the small-series SCM research (see Figure 2.4). Supply chain coordination by various means is integral to achieving a significant reduction in the operational and production costs and to the effective management and business growth (Tanimizu, 2014). The articles falling under this theme highlight simulation methods as the predominantly successful and effective methods for dynamically studying the coordination of SC agents in the MTO system. Effective SC coordination strategies are critical for MTO SCM

as they can influence consumer preferences and satisfaction positively through high-quality product delivery. Consumer demand for MTO products is sensitive to the way SC coordination among the suppliers and retailer is managed based on effective negotiations considering common business goals, resource and information sharing and profit-sharing. One of the key policies utilized for achieving effective SC coordination in MTO production system is by adopting decentralized decision-making approach, where each SC actor can make a decision based on the targeted profit goal while contributing to the goals of the other actors (Giannoccaro & Pontrandolfo, 2004).

The commonly agreed-upon policies and alignment practices for SC coordination play a crucial role in handling the conflict between SC actors, and it can significantly avoid the scenarios of SC disruptions and risks (Castelli & Brun, 2010). SC coordination is interlinked with production planning in MTO context from the perspective of operational management. Overall, in the selected articles, the major emphasis is given on the information sharing and negotiations among SC actors as the key problems.

Table 2.2: Summary of articles in supply chain coordination theme

Source	Research Problem	Method	Summary
(Kobayashi et al., 2017)	MTO production planning	case study	Strategies for collaboration with external as well as internal partners are outlined.
(Tanimizu, 2014)	Coordination protocol to decide prices and lead time for the orders	simulation technique	Three-layered SC model is effective to handle coordination problems.
(Xiao et al., 2014)	study the impact of price and lead time on SCM coordination	game theory	SCM coordination is achieved by studying the dynamics of lead time and price changes.

(Hempsch et al., 2013)	customer order fulfilment	a multi-agent-based system, multi-attribute multi-utility simulations into a linear program	An effective solution is proposed to formulate strategic negotiations when customer orders are difficult to fulfil.
(Tokta-Palut & Ülengin, 2011)	to coordinate inventory policies	optimization methods	The backorder and holding cost subsidy contract, the transfer payment contract, and the cost-sharing contract are found to be effective for SC coordination.
(Xiao et al., 2011)	optimize service quality and pricing decisions	conceptual model	The effects of defective product rates are studied in relation to negotiation between SC agents.
(Forsman et al., 2011)	finding the remedies for SC deficiencies in terms of information sharing	review study	Increased improvement in the interactions among suppliers is effective to develop better production strategies.
(Kuroda & Kida, 2010)	to formulate SCM coordination decisions in multi products environments	conceptual model	Customer-manufacturer decision strategies to lower the loss arising out of customers independent buying choices are developed.
(Foreman et al., 2010)	optimize supply routes	mixed-integer programming	The proposed solution has significantly reduced the company's inventory repositioning cost.
(Bui et al., 2009)	to automate multi-attribute co-ordinations in order fulfilment	Multi-agent simulation method	Effective negotiations are significant for reducing the return rate and improving revenue.
(Gunasekaran & Ngai, 2009)	to model MTO SC	Literature Review methods	Existing literature on MTO Supply chains is studied.

(Özbayrak et al., 2007)	to model SC networks for MTO SC	system dynamic study	Model for measuring the SCM system performance considering key factors such as inventory, WIP levels, backlogged orders and customer satisfaction.
(van der Vaart & Wijngaard, 2007)	to study the factors responsible for the loss of pooling synergy with the advantage of focus	simulation technique	The study concludes that the set-up time reduces the positive effects of pooling while the focus is beneficial in case of large set-ups.
(Stevenson & Hendry, 2007)	to identify the research gaps in regard to SCM decision making in information sharing scenarios	Literature Review	Ten propositions are suggested for future researches in the integration of the internet as a tool for information sharing.
(Hyun et al., 2006)	to assign orders to suppliers based on optimal resource allocations strategies of the suppliers	SET model	Optimal solutions for deciding production costs depending on lead times have been developed so that all the agents in the SC are better off.
(Azambuja et al., 2006)	to investigate as to how the commitments among SC members impact the very process of SC integration for MTO production system	Literature review	Language Action Perspective (LAP) analysis is used to better integrate the commitments among SC agents for MTO system.
(Schneeweiss & Zimmer, 2003)	to analyze operational coordination strategies between suppliers	conceptual model	Information sharing among the SC agents is critical to achieving SC coordination for MTO production setting

(“IFIP TC5/WG5.3 2nd IFIP Working Conference on Infrastructures for Virtual Organizations: Managing Cooperation in Virtual Organizations and Electronic Business towards Smart Organizations,” 2001)	to manage SCM co- operations in virtual manufacturing systems	optimization models	various methodologies for achieving optimal co- ordinations across MTO SCs have been proposed and discussed.
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2.3.1.3 Order planning

MTO product orders are dynamically generated by the customers, and they are the representative of their specific preferences, which pose various challenges for the efficient order fulfilment planning. In the articles constituting the theme of order planning, the issues in the MTO order planning range from determining the order in which the customer orders to be processed and estimating the lead time to resource allocation and profit maximization. Dynamic processing of the customer orders of MTO products with a high degree of variability in terms of customization level is a challenging task from the point of view of strategic SCM (Khakdaman et al., 2015).

Table 2.3: Summary of articles in order planning theme

Source	Research Problem	Method	Summary
(Khakdaman et al., 2015)	multi-product production planning	multi-objective optimization model + Linear programming	Proposed linear programming based multi-objective optimization model is applied for multi-product multi-period production planning problem-solving.

(Venkatadri et al., 2008)	to determine delivery dates for the customer orders	optimization model	The optimization model is developed to quote order due dates for the customer orders
(G.P. Cachon & Zhang, 2007)	to study the performance of demand allocation to enable fast queueing	literature review	an optimal order allocation policy based on servers' quick response strategies is studied.
(Kirche et al., 2005)	to maximize SC profit with optimal resource allocation	mixed-integer programming	An optimization model for cost with the constraints of resources and capacity for MTO manufacturing system is developed.

2.3.1.4 Sales and operation planning

Sales and operation planning is an under-explored research area in MTO production system. Efficient and accurate forecast of customer demands and the uncertainties associated with consumer behaviour are the important SCM tasks related to sales and operation planning in many retail industries. Sales forecasting is one of the difficult and most challenging tasks in the retail industry given the heavy dependencies of operational and production planning on accurate sales and demand forecasts (Thomassey, 2010), (N. Liu et al., 2013). However, in a general MTO industrial framework, forecast models are less relevant for long term demand or sales prediction as the customer preferences are of dynamic nature and highly volatile, and therefore, new models for tracking consumer preferences in a real-time are needed. Simulation-based methods can help industries to gauge the dynamics of customer demands and help formulate their sales planning strategies based on abstract results drawn from simulation results. Simulation-based models for sales and operation planning help manage customer demand uncertainties (Feng et al., 2010).

Table 2.4: Summary of articles in Sales and operation planning theme

Source	Research Problem	Method	Summary
(Feng et al., 2010)	SCM performance evaluation	simulation technique	Realistic solutions for effectively managing demand uncertainties are proposed.

2.3.1.5 Sustainability

Despite the growing worldwide emphasis on sustainability issues and primary concern for ecological balance and sustainable consumption that drives MTO industry trends in many industry sectors; research literature on sustainability management in MTO framework is rather limited. Decision problems aimed at tackling sustainability problems are often related to effective carbon emission control from production and transportation activities, Life Cycle Assessment (LCA) of MTO products, sustainable waste management, and alignment of production and operational level decisions with sustainability constraints, etc. (Strähle & Müller, 2017), (Qiao et al., 2019).

Table 2.5: Summary of articles in the Sustainability theme

Source	Research Problem	Method	Summary
(Qiao et al., 2019)	optimization for lot size	optimization	Carbon management has been achieved by constrained optimization.
(Strähle & Müller, 2017)	outsourcing decision + Quick Response strategy	Multi-agent simulation	Improvement in sustainability.

2.3.2 SCM in the small-series fashion industry

Following the same systematic literature review approach as described in Section 2.3.1., the existing literature on the studies on supply chain management in small-series (make-to-order) fashion industry is collected using the *Scopus* database. This approach is used to explore the current status of research trends of SCM, specifically in the fashion industry. Peer-reviewed journal articles are retrieved from the Scopus database with the search strings comprised of thesis topic related terms as shown in the search input given below;

("supply chain management") AND ("for" OR "in") AND ("small-series" OR "make-to-order") AND ("fashion" OR "Apparel" OR "clothing" OR "textile" OR "garment") AND ("industry")

Although many interchangeable terms for fashion industry such as “textile”/ ”clothing”/ “apparel”/ “garment” are used in the search string to ensure that the complete list of articles related to the topic is generated from the database, the search resulted into a very limited number of studies on small-series (MTO) fashion SC. It implies that the thesis topic is highly relevant as there exists limited literature on the SCM problems in the small-series fashion industry.

The search input yielded only four articles, as summarized below. Consequently, four articles are used to review the current status of research in the area related to the thesis topic.

Following figures; Figure 2.5; Figure 2.6; and Figure 2.7 show the distribution of collected papers as per the year of publication; type of publication; and the subject areas respectively.

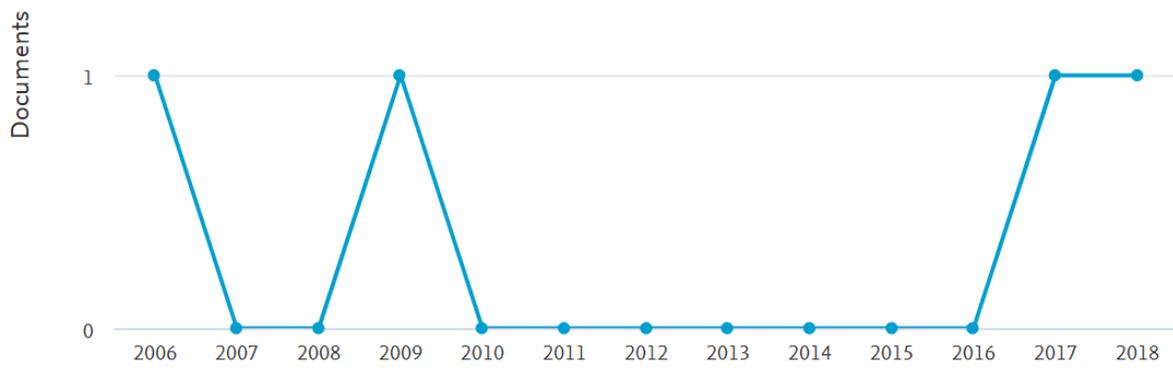


Figure 2.5: Scopus peer-reviewed papers by year of publication

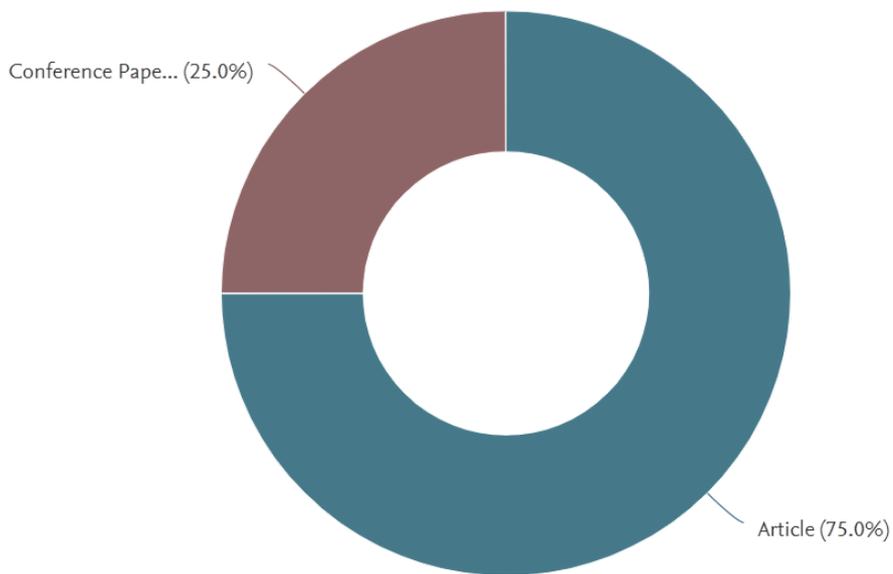


Figure 2.6: Scopus peer-reviewed papers by types

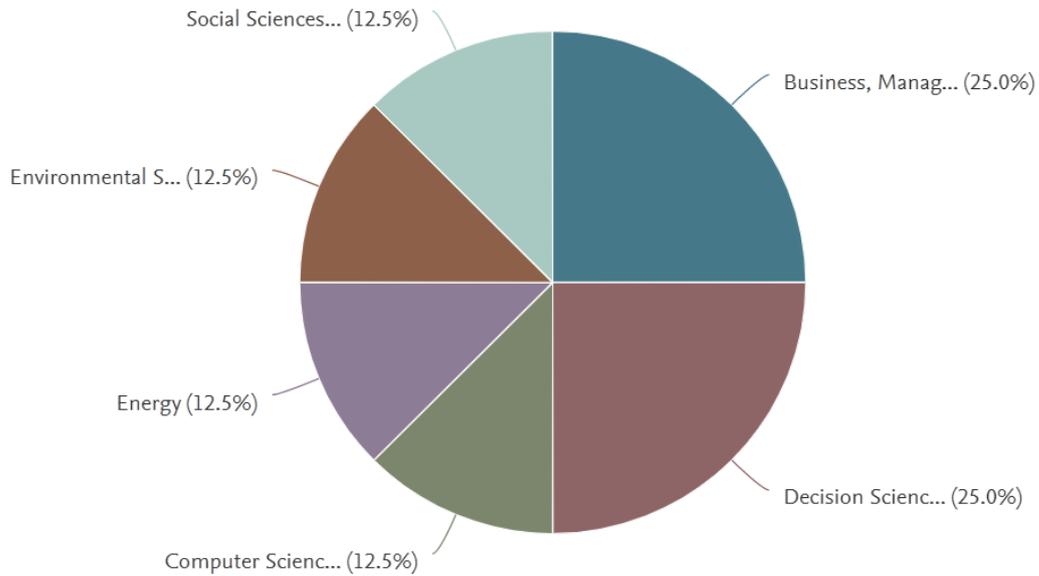


Figure 2.7: Scopus peer-reviewed papers by subject area

Based on the review of collected articles, two common themes are found as in the review of studies in other industries (see Section 2.3.1) and are discussed below.

2.3.2.1 Production planning

As discussed in Section 2.3.1.1, production planning is the crucial element of SCM and is found to be an important one in the small-series fashion industry as well. From the perspective of developing quick response (QR) SCM strategies, inventory risk management is the key problem in production planning theme and thus is highly challenging. There is a growing emphasis on not only having a QR system in place but also on building more accurate QR system in order to effectively control SCM risks. (T.-M. Choi, 2018) explores the risk-averse behaviour of fashion retail suppliers in the MTO framework and proposed the solution for minimizing their inventory management risks arising out of volatility of consumer demands. This study explored the impacts of QR solutions on the entire SC in terms

of their expected business goals. Moreover, it highlighted that the risk-averse behaviours of certain agents in the SC could be dangerous for other agents as they are highly interdependent, and by embedding their risk-averse behaviour into an optimization model, inventory risks can be effectively controlled. Another decision problem, as explored in (Wong & Leung, 2006), is related to optimizing the carton sizing for MTO customer orders. Genetic algorithm has been applied in this study to minimize the unfilled space in the carton boxes and optimally design the box dimensions according to the varying dimension of MTO products.

Table 2.6: Summary of articles in production planning theme

Source	Research Problem	Method	Summary
(T.-M. Choi, 2018)	to explore the impact of MTO fashion retailer's risk behaviour on SC systems	optimization method	Optimal decisions of risk-averse MTO fashion retailers are studied, and significant insights into how they manage their replenishment and develop quick response strategies while negotiating with the suppliers are derived.
(Wong & Leung, 2006)	to optimize the production of carton boxes, used in packing fashion products of varying sizes	Genetic algorithm	With the application of applied Genetic algorithm, the cost of overall packaging and distribution process has been minimized.

2.3.2.2 Supply Chain Co-ordination

Similar to other MTO industries, SC co-ordination is the second main research theme in the small-series fashion industry as evident from the study of collected literature articles. As

concluded by (Ma et al., 2017), SC co-ordination strategies play a key role in the improvement of SC performance in the small-series fashion industry. In the same study, a central order processing system (COPS) is developed to optimize SC performance by means of simulation modelling on real fashion SC data, and the results explored the effects of COPS system on SC performance in various scenarios such as focusing on seasonal dynamics and different echelons of the SC, subsequently identifying the factors improving the performance of COPS. As the SC co-ordination implies the trustworthy relationships among fashion suppliers, MTO environment compels small-series fashion industry to develop agile and QR SC co-ordination strategies based on strategic negotiations with the SC partners, information sharing and trust (de Leeuw & Fransoo, 2009). Enabling coherent collaboration among all the involved SC actors is critical to achieving efficient SCM and customer satisfaction. In a typical mass fashion production context, various contract policies have also been utilized to avoid SC disruptions owing to conflict of interest among SC actors, for example, in (Yan et al., 2016), buy-back contract efficiently coordinates the SCM system quite than in the case of wholesale price contracts. However, in the MTO system, there are a great number of future opportunities to integrate these contract-based policy aspects in small-series fashion SC co-ordination.

Table 2.7: Summary of articles in supply chain coordination theme

Source	Cluster	Research Problem	Method	Summary
(Ma et al., 2017)	Supply Chain co-ordination	to develop a sustainable MTO fashion SC	multi-agent simulation method	Proposed simulation model demonstrated the advantage of collaborative cloud platform in achieving sustainability goals of the SC.
(de Leeuw & Fransoo, 2009)	Supply Chain co-ordination	to investigate as to what factors are important for the close SC collaboration	Conceptual model	When the close collaborative SC system is in place, it can drive MTO fashion firms to make optimal choices while managing their business operations.

2.4 Analysis of literature review and research opportunities

Based on the broad literature study, it is evident that the key aspects of small-series fashion SCM have been given an adequate attention such as production planning; SC co-ordination, order and sales planning; and to some extent to the sustainability aspect. However, there are important areas such as the selection of suppliers for raw materials and customized fashion products and dynamic customer order allocations in the small-series (MTO) fashion that have not been adequately investigated. As the fashion industry is undergoing huge transformation due to the advent of ICT technologies and the automation trends in the Industry 4.0 framework, it is substantively interesting to study how small-series fashion retail industries select their SC partners, especially their suppliers, and what are the driving factors behind their partnership with them. In addition, how small-series fashion companies use customer data, customer order data in particular, to align their requirements with the capacity of their suppliers thus selecting the best matching suppliers provide plenty of significant avenues for research. The existing studies do not address these new developments within the fashion industry, especially the small-series fashion industry framework that requires agile, automated, and effective decision models to solve the key SCM decision problems.

E-commerce platforms enable fashion companies to collect and exchange data with their customers and partners, such as designers and suppliers and to provide high-quality products and services to their customers (Bruce & Daly, 2010). Small-series fashion is predominantly based on the e-commerce business model; therefore, the study of how small-series fashion companies select their suppliers and how they allocate dynamic customer orders constitute a highly relevant research topic. Moreover, given the growing research trend of investigating applications of AI in various industries for solving important decision problems, particularly for forecasting sales and customer demand predictions in mass-scale production systems, it is

clear that such areas of research focusing on applications of AI in small-series fashion SCM system remain under-investigated. These topics have not received sufficient attention in the existing literature. Ideally, small-series fashion retailers need to retain their customers' loyalty by providing with the high degree of shopping satisfaction through the delivery of best quality products at the right time. It implies that they need to possess advanced methods and tools to make real-time decisions related to the customer order fulfilment, which are order assignment and selection of best supplier. Overall, it seems to be the substantial challenge to explore this dimension of small-series fashion industry's SCM problems as there are near to none of the reported studies on this subject.

Beside supplier selection, the scientific methods that could be suitable to enhance decision making related to customer order classification and allocations are worthwhile to be examined in the context of SCM in the small-series fashion industry. There are plenty of research opportunities in studying decision-making paradigms in e-commerce small-series fashion. Unlike the mass scale fashion production systems, small-series fashion is an under-explored research area, and therefore it is interesting to undertake the study as to how the current technological trends are shaping the industry and what challenges they pose for various decision problems including the ones that are clearly highlighted in this section. Given the highlighted reasons, it is worth examining the underlying mechanism that improves SCM in small-series fashion. Furthermore, another interesting research opportunity lies in the domain of AI that could develop an effective solution for the supplier selection problem using customer order data, and in particular, how the decision variables for selecting suppliers evolved from the traditional fashion setting to the current trend of small-series fashion.

Overall, this thesis primarily aims to extend the boundaries of existing literature by contributing to solving the three research questions, as outlined in Chapter 1, as they promisingly provide good scopes and directions for the new and original research. In this

thesis, an experimental research approach is used to develop an effective mechanism based on MCDM, ML and GA methods to solve firstly, the raw material and garment supplier selection problem, and secondly, the dynamic customer order assignment problem. It is of great importance to broadly investigate the supplier selection and customer order management problems in the small-series fashion SCM as they constitute the novel research themes that have not been investigated in the existing studies. Therefore, the main contributions of the research conducted in this thesis is (1) to select raw material suppliers for the small-series fashion products in a static way, (2) to classify the suppliers as per the best match with the new customer order, and finally (3) to dynamically assign new customer orders to the best garment suppliers.

Chapter 3

Methodology

This chapter provides the background of the scientific research methods implemented in this thesis. The main scientific methods used for addressing the research questions are described in detail, focusing on their theoretical background and mathematical formulations.

Literature review, presented in Chapter 2, and three formulated research questions, as presented in Chapter 1, guide the methodological approach and research design of this thesis. The first research question (RQ1) aims to develop a mechanism by which small series-fashion retailers select their raw material suppliers in a static way based on various criteria essential for their business goals and strategies. The developed mechanism could be implemented for raw material supplier selection for massive replenishment of fashion material with a low frequency. In such a situation, the criteria for raw material supplier selection are considered as "static" since they are broad qualitative features which are not updated frequently. This implies that RQ1 constitutes a multi-criteria decision problem for which the Multi-criteria Decision Method (MCDM) based methods such as AHP, TOPSIS and Fuzzy-TOPSIS, as elaborated in Section 3.1, are applied to address it.

Secondly, the second research question (RQ2) is to predict the best suitable supplier for a customer order for small-series fashion item in a real-time based on historical e-commerce sales data obtained from a small-series fashion company. The methodological consideration for addressing RQ2 is based on Machine learning (ML) based algorithms owing to its efficiency and popularity for solving prediction problems (James et al., 2013). The detailed mathematical formulations of chosen ML methods are described in Section 3.2.

The third research question (RQ3) addresses the problem of dynamic order assignment to the best small-series fashion garment supplier in a way that retailers' business objectives are fulfilled. Evolutionary algorithm (EA) such as meta-heuristic based Genetic Algorithm (GA) method is used for investigating this research problem because of its ability to find high-quality optimal solutions (Horn et al., 1994). GA-TOPSIS model is applied to enable the scope for the retailers to use their data encapsulating their historical performance-related judgments of their suppliers and aid dynamic order assignment problem solving based on the input data. The genetic algorithms are advantageous for solving optimization problems given their unique ability to retain a population of computed solutions and improve them over several generations represented in terms of genetic chromosomes. GAs are the heuristic methods popular for finding high-quality optimal solutions for the search optimization problems by going beyond local minima (Gu & Sun, 2018). The description of the illustration of the GA method is presented in Section 3.3. Finally, the summary of the chapter is presented in Section 3.4.

The research questions, as described earlier, data and the objectives in this thesis guide the methodological approach followed in this thesis. The nature of the data used to address RQ1, RQ2 and RQ3 respectively is both qualitative and quantitative, and it also includes experience or observation-based data (Chapter 4), therefore, mixed and exploratory methodological framework (Aldag & Steams, 1988), (Scandura & Williams, 2000) is applied in this thesis. Another aspect of the research methodology used in this thesis is experimental approach (Eiben & Jelacity, 2002) as different decision scenarios are developed to solve the research questions in this thesis in which a few factors are controlled, and the results are produced accordingly.

3.1 Multi-criteria decision methods (MCDM)

MCDM methods are widely used for making evaluations of different solutions or alternatives from multiple aspects and for making recommendations based on this evaluation. Supplier selection problem is an MCDM problem since it involves the evaluation of a finite set of potential suppliers based on a multitude of criteria and their ranking according to score calculations. Most popular MCDM methods are AHP and ANP (known as multi-attribute utility methods); Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) and Multi-criteria Optimization and Compromise Solution (VIKOR); and Elimination and Choice Expressing Reality (ELECTRE). The detailed description of these methods can be studied in (Lee & Chang, 2018). The integrated MCDM methods such as Fuzzy-AHP, Fuzzy-TOPSIS, which are primarily based on fuzzy number set theory can be referred in (Kaya et al., 2019).

The MCDM methods; AHP and Fuzzy-TOPSIS applied to address the RQ1 are described in the following sections, i.e. 3.1.1 and 3.1.2.

3.1.1 AHP

The analytic hierarchy process (AHP) is a method for evaluating complex decisions grounded on psychology and mathematics, developed by Thomas Saaty. It is considered as the robust multi-criteria decision-making technique and widely applied in the field of engineering decision making science and operation management (Saaty, 2008)(Saracoglu, 2013).

The AHP method for the MCDM strategy is an effortlessly justifiable, discerning and deliberate one. This characterizes an arrangement in reliable networks in the method consists of pairs of adages, decreases a hugely problematic issue into a more organized organization of simple perception and promotes a more functional methodology.

In the scholarly group, AHP is widely disseminated and linked to specific fields such as engineering, medicine, and other sciences (Karthikeyan et al., n.d.).

This represents the most precise way of assigning a value signifying preference degree for a particularly given alternative to each added alternatives, respectively (Chai et al., 2013). AHP offers a structured framework that helps the decision-makers to make a rational decision. First, decision-makers have to prioritize the best suitable goal based on their problem and then quantify its elements with the large goals for assessing the alternatives.

Steps to use the AHP are outlined below:

1. Define the criteria sub-criteria for your problem.

This is the first step to be determined and to define the decision goal as *G*.

2. Considering the decision goal *G* at the highest, create a hierarchy with several evaluation criteria $C = \{C1, C2....Cn\}$ and sub-criteria in the center, and alternatives $A = \{A1, A2....An\}$ at the lowest, as shown in Figure 3.1.

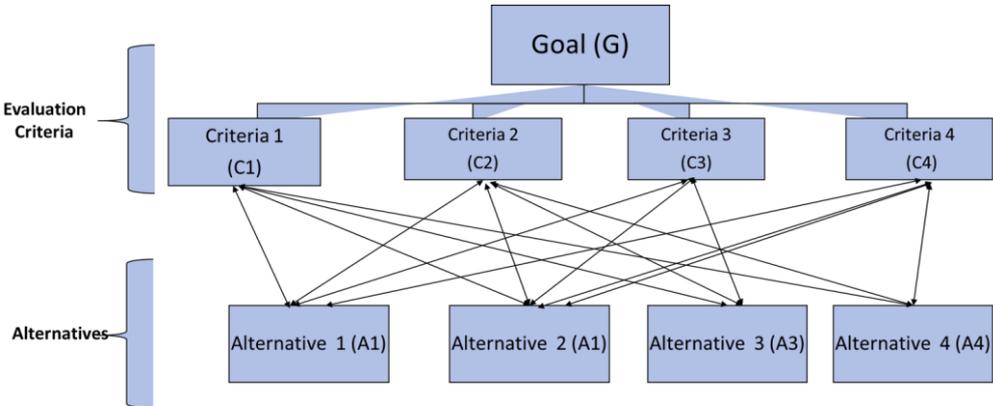


Figure 3.1: Hierarchical structure of AHP model (Vidal et al., 2011)

3. Performance Analysis:
 - a. Make a pairwise comparison of criteria (*C*) based on their significance in accomplishing the final goal and identify the priorities among them.

- b. Make a pairwise comparison of the alternatives (*A*) based on their significance, fulfilling the evaluation criteria and identify priorities among them.

Once the hierarchy is formulated, the next stage is evaluating the criteria (*C*) in a pairwise manner by the evaluators. Weights ($W = \{W_1, W_2, \dots, W_n\}$) of the criteria are assigned with the help of Saaty's Scale (Saaty & Peniwati, 2008). Hence, the expert decision is required to assign the weights to the elements.

Intensity of Importance	Definition
1	Equal importance
3	Slightly more important
5	Much more important
7	Very much more important
9	Extremely more important
2, 4, 6, 8	Intermediate values

Figure 3.2: Saaty's pairwise comparison scale

The weight assessment helps to determine the numerical priorities among the numerous evaluation criteria and the alternatives. Firstly, one needs to perform the pairwise comparison assessment using the Saaty's scale, as shown in Figure 3.2. The number of comparison elements relies on the number of criteria (*C*) studied for a given problem, and it can be defined as shown below in Equation 3.1;

$$\text{No. of Pairwise comparison} = \frac{n(n-1)}{2} \quad (3.1)$$

Where *n* is the number of criteria (C_n) that are compared

After doing the pairwise comparison analysis, the next stage is to create a relative weight matrix; that is a different weight (W) allocated to each criterion depending on their importance, as shown in following equations;

$$\text{Pairwise Comparison Matrix } C_{n \times n} \begin{bmatrix} W1/W1 & W1/W2 & \dots & W1/Wn \\ W2/W1 & W2/W2 & \dots & W2/Wn \\ \dots & \dots & \dots & \dots \\ Wn/W1 & Wn/W2 & \dots & Wn/Wn \end{bmatrix} \quad (3.2)$$

$$\text{Weight Matrix } X_{N \times 1} \begin{bmatrix} W1 \\ W2 \\ \dots \\ Wn \end{bmatrix} \quad (3.3)$$

Then,

$$\begin{bmatrix} W1/W1 & W1/W2 & \dots & W1/Wn \\ W2/W1 & W2/W2 & \dots & W2/Wn \\ \dots & \dots & \dots & \dots \\ Wn/W1 & Wn/W2 & \dots & Wn/Wn \end{bmatrix} \begin{bmatrix} W1 \\ W2 \\ \dots \\ Wn \end{bmatrix} = \lambda \begin{bmatrix} W1 \\ W2 \\ \dots \\ Wn \end{bmatrix} \quad (3.4)$$

Where,

$W1, W2, \dots, Wn$ are relative weights for the n criteria.

The matrix can be represented by Equation 3.5;

$$AX = \lambda X, \quad (3.5)$$

$\lambda = \text{Eigen value of matrix } A_{n \times n} \text{ and}$

$X = \text{right Eigen vector of matrix } A_{n \times n}$

$n = \text{Eigen values of Matrix } A_{n \times n} \text{ and its Eigen vectors}$

Therefore, Equation 3.5 is transformed into Equation 3.6 as shown below;

$$(A - \lambda I)X = 0 \quad (3.6)$$

Next, the determinant of $(A - \lambda I)$ is computed as $|A - \lambda I| = 0$

$$\text{Where } I \text{ (Identity Matrix)} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.7)$$

Pairwise comparison matrix table for $A_{n \times n}$ is shown in Table 3.1 below;

Table 3.1: Pairwise comparison matrix for criteria

	W1	W2	Wn
W1	W1/W1	W1/W2	W1/Wn
W2	W2/W1	W2/W2	W2/Wn
....
Wn	Wn/W1	Wn/W2	Wn/Wn

Here, the diagonal values of the matrix will be 1, and other values of the matrix will be based on relative weights of the criteria.

Rank the alternatives based on overall priority from the results of steps 2 and 3.

4. Take the alternative selection decision using the following steps;
 - a. For each alternative, multiply the weight of criteria corresponding to an alternative from the final goal's perspective.
 - b. Subsequently, taking the sum of all the products resulting from 'step a' yields the overall priority weight of each alternative.
 - c. Normalization of columns of $N \times N$ matrix is done by dividing each column element by the sum of that column.

$$[\text{Matrix } A]_{n \times n} \xrightarrow{\text{Normalization}} [\text{Matrix } B]_{n \times n}$$

- d. Average of each row of the normalized matrix is computed, which results in $N \times 1$ matrix, which has a priority Eigenvector that contains the overall weight of each criterion.

$$[\text{Matrix } B]_{n \times n} \xrightarrow{\text{Averaging rows}} [\text{Matrix } X]_{n \times 1}$$

Decisions can be made at this stage by selecting the highest ranked criteria and alternatives.

Based on the literature referred in this section in regard to the AHP method, its strengths and limitations are summarized in Table 3.2.

Table 3.2: Advantages and disadvantages of AHP method

Strength	Weakness
It's wide usability.	AHP makes use of accurate judgment quality. That is to say, in use cases, human emotions are obscure, and the authorities may not be able to determine the careful numerical quality of the examination judgments. AHP is not significant in this scenario.
It's a system that is effortlessly reasonable.	It can only set up direct models. In other words, one whose output is precisely consistent with its information. It can't unravel non-direct models. That is to say, one whose result is not directly consistent with its information—for example, the Weather Gauge.
It unravels the complicated issue by separating it into smaller steps.	The AHP can only recognize free criteria for pairwise correlations. The AHP is unable to consider uncertainty and threat when an expert decides on a choice, on the ground that nature is conflicting for all purposes and objectives, and the decision-making process is designed only with respect to the present circumstances and the expert's intuition.
Authentic information sets are not required.	If there is an extension or deletion of the option or rule, the query for a rank may differ.
The AHP system provides a simple path for the scholastic to take care of complicated issues.	The decision should be taken clearly in light of the previous knowledge of the expert. The preferential decision of the expert and change of scale can have an effect on the final outcome of the AHP.

The AHP method is chosen for the evaluation and ranking of raw material supplier selection criteria because of the appropriate nature of the inputs that could be developed based on the qualitative judgements of the decision makers on the relative importance of criteria.

Moreover, the Saaty's scale used in the AHP method enables decision maker to evaluate the relative importance of the supplier selection criteria with respect to each other and AHP method aggregates their individual priority scores (Saaty, 2008). The decision matrix used for the evaluation of raw material supplier selection criteria is created using decision makers qualitative judgements, for which AHP is the most suitable method to quantify these judgments (Y. Chen et al., 2013). It follows an efficient knowledge-based approach that enables the transformation of qualitative knowledge of the decision makers into quantitative information. This approach is required in the MCDM problem where multiple conflicting criteria are involved in the decision analysis. The raw material supplier selection decision is based on the multiple criteria and identification of the most important criteria out of them is crucial for the supplier evaluation. Therefore, the AHP method is selected to evaluate the criteria to find the most important ones based on decision makers' judgements.

3.1.2 Fuzzy-TOPSIS

Fuzzy-TOPSIS method is an MCDM method, which is based on the fuzzy numbers used for transforming linguistic variables into triangular fuzzy numbers (Ateş et al., 2007). The mathematical formulation for Fuzzy-TOPSIS method is described in the following subsections.

3.1.2.1 Fuzzy Sets and Fuzzy Number

Fuzzy Sets are used to map the uncertainty of real-world problems, which can be subjective or vaguely defined. This was introduced by Zadeh (Zadeh, 1965) as an extended version of classical set theory. This theory is further extended and intensively applied since 1970 (Gottwald, 2010). Its applications and implementations are widely used in data analysis, Artificial Intelligence and operation research.

The fuzzy set can be defined as (U, m) , where U is a defined as a universal set and each member in this set assigned m as membership function lies between 0 and 1 and can be represented as $U \rightarrow [0,1]$ (Dubois et al., 1980). Let's consider a fuzzy set, $X = (U, m)$, then the member function will be $m = \mu(E)$ and will assign the values between 0 and 1 to each elements. Membership functions for each elements e for a finite set $U = \{e_1, \dots, e_n\}$, can be written as $\{m(e_1)/e_1, \dots, m(e)/e_n\}$. If $e \in U$ and $m(e) = 0$, then the element e will not be considered in $X = (U, m)$, and while $m(e) = 1$, it will be considered fully and fractional consideration will be done if $0 < m(e) < 1$ (Beg & Ashraf, 2009).

Fuzzy sets allow scientific operations of intersection, complement and union. It follows the mathematical operation of complement, intersection and union. For the fuzzy set X and Y , $X, Y \subseteq U$, $u \in U$, complement operation can be represented as $\mu_X(u) = 1 - \mu_X(u)$, intersection operation can be represented as $\mu_{X \cap Y}(u) = \min\{\mu_X(u), \mu_Y(u)\}$ and Union of two fuzzy sets can be shown as $\mu_{X \cup Y}(u) = \max\{\mu_X(u), \mu_Y(u)\}$ (Gottwald, 2010). Fuzzy sets have “Commutative”, “Associative”, “Distributive”, “Identity property” and “Transitive Property” (Gottwald, 2010). Triangular membership is one of the popular methods and widely applied for solving the engineering problems due to its flexibility (Pedrycz, 1994).

For a fuzzy set Y , degree of the Membership function is illustrated in Figure 3.3, and equations for the lower and upper limit, a and b as $a < b < c$ are denoted in Eq. 3.8.

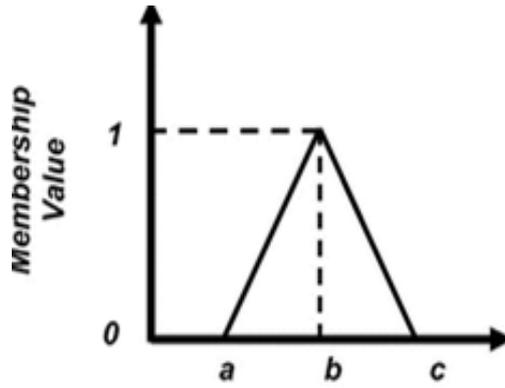


Figure 3.3: Fuzzy triangular membership function

$$\mu_Y(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x < c \\ 0 & x \geq c \end{cases} \quad (3.8)$$

3.1.2.2 TOPSIS

TOPSIS (Technique for Order of Preference by similarity to Ideal solution) is developed by Ching-Lai Hwang and Yoon and is a multi-criteria decision analysis technique (Hwang & Yoon, 1981)(Yoon, 1987). TOPSIS was first proposed in crisp version as a linear weighting technique, and after that, it is commonly used to solve the Multi-Criteria decision problems (MCDM) in various engineering and management fields (Bottani & Rizzi, 2006)(Chaghooshi et al., 2012).

It works on the principle of geometric distance for selected alternatives; the shortest distance is the positive ideal solution, and the largest is the negative ideal solution (NIS) (Chaghooshi et al.2012). Geometric distances are calculated and summed, and alternatives are chosen based on maximum similarity. Most of the times, experts find it difficult to allocate the score to the alternatives that are considered for the evaluation. Therefore, the fuzzy approach gained

importance for fuzzy numbers over-allocating a precise score. This research study uses the fuzzy triangular numbers, and for the middle value, the average is used for the lower and upper bound.

Detailed mathematical formulations of Fuzzy-TOPSIS method given below are adopted from (T. C. Wang & Chang, 2007).

Step 1: Define the weights, $W = \{W1, W2, W3, \dots, Wn\}$ of the evaluation criteria.

Step 2: Create a Fuzzy Matrix as shown below

$$\tilde{D} = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 & \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ A_2 & \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_m & \tilde{x}_{m1} & \tilde{x}_{m2} & \vdots & \tilde{x}_{mn} \end{matrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

\tilde{x}_{ij} is the score of alternatives A_i for the corresponding criterion C_j

Step 3: Fuzzy decision tree normalization is shown below, where \tilde{R} represents the normalized fuzzy matrix.

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}, i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

Where,

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{c_j^+}, \frac{m_{ij}}{c_j^+}, \frac{u_{ij}}{c_j^+} \right), c_j^+ = \max_i c_{ij}$$

Step 4: Build a weighted normalized fuzzy matrix \tilde{V} as represented below

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$$

Where \tilde{w}_j is the weight of criterion C_j

Step 5: Identify the FPIS (Fuzzy positive-Ideal solution) and FNIS (Fuzzy negative-ideal solution)

Here, as positive triangular fuzzy numbers are used for the interval [0, 1], ‘Fuzzy positive ideal reference point ($FPIS, A^+$)’ and ‘Fuzzy negative ideal reference point ($FNIS, A^-$)’ can be represented as below;

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_n^+)$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-)$$

Where, $\tilde{v}_1^+ = (1,1,1)$ and $\tilde{v}_1^- = (0,0,0), j = 1,2, \dots, n$.

Step 6: Compute the geometric distance for all alternatives A_i from FPIS and FNIS. Area compensation technique is used to determine the distances d_i^+ and d_i^- of alternative A^+ from A^- as shown below;

$$d_i^+ = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^+), i = 1,2, \dots, m; j = 1,2, \dots, n$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), i = 1,2, \dots, m; j = 1,2, \dots, n$$

Step 7: Determine the closeness co-efficient, CC_i . Based on that, the order of alternatives A_i will be ranked, by which the decision-makers can make the right decision. Closeness co-efficient can be calculated as below;

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1,2, \dots, m$$

The disadvantages of TOPSIS method were raised in the inability to measure the complex weights of the parameters, and thus a hybrid approach based on fuzzy and TOPSIS was used for risk assessment (Barros & Wanke, 2015; Kumar et al., 2017).

With reference to the literature cited for TOPSIS and Fuzzy methods description, their advantages and limitations are summarized in Table 3.3 and Table 3.4, respectively.

Table 3.3: Strength and weakness of the TOPSIS method

Strength	Weakness
It works with the basic ranking.	Basically, it works on the basis of the Euclidean distance and thus does not consider any difference between negative and positive values.
Make full use of allocated information.	The value of the attributes should be monotonically increasing or decreasing.
The information must not be independent.	

The TOPSIS method is selected to evaluate raw material suppliers based on both qualitative and quantitative criteria. For the analysis of raw material suppliers, quantitative data on some of the criteria could be passed into the decision matrix in addition to the qualitative judgements of the decision maker. The TOPSIS enables the decision maker to prioritize the business objectives while evaluating the alternatives. As the first step, the qualitative judgements of the decision maker on the supplier selection criteria constructed with the AHP can be passed to the TOPSIS as an input for the supplier evaluation (Hajek & Froelich, 2019). Therefore, this unique mechanism of the TOPSIS method is suitable for solving the raw material supplier evaluation problem that is addressed in RQ1.

Table 3.4: Strength and weakness of Fuzzy method

Strength	Weakness
It works with the abstract mathematical functions.	The exponential growth of rules
Linguistic representation of the data	Accuracy decreases as the number of rules increases.
Easy programming	Complex rule chaining problems

As illustrated earlier, the Fuzzy-TOPSIS is a hybrid method that builds on the fuzzy set theory and works in conjunction with the TOPSIS method. This method is chosen to handle the

uncertainty in the aggregation of decision makers' judgements on the criteria and the suppliers. In RQ1, multiple decision makers participate in the decision making process that involves multiple criteria and suppliers. The choice of the Fuzzy-TOPSIS method is appropriate to implement this decision scenario because it takes into account fuzzy and ambiguous judgements of the participating decision makers and transforms them into fuzzy numbers to produce realistic result analysis. The input data for the application of the Fuzzy-TOPSIS method is presented in Chapter 4, which is specific to the Fuzzy-TOPSIS method approach.

3.2 Machine learning (Supervised classification models) methods

Machine learning is the technical study of computer algorithms, through which machines are trained to solve the tasks without being explicitly programmed and without human intervention (Bishop & M., 2006). ML algorithms learn from the historical data for finding the hidden patterns and make insightful predictions. Machine Learning Analytics pipeline is shown in Figure 3.4. It is comprised of several steps such as data collection, pre-processing, feature engineering, model training and model evaluation. At the stage of modelling, multiple models can be used and evaluated as per the data features. Based on the comparative results, the best model can be selected, which can be integrated and developed as an application for commercial use. The process shown in the below figure is iterative in nature and can be repeated multiple times unless the defined business problem is resolved. For example, after the feature engineering step, data attributes are selected as a feature for a particular target variable. After exploratory analysis step, which analyzes the relationship among the variables (correlation), if some of the data attributes show weak relationships, it's good to remove such attributes as they can affect the performance of the ML model. Figure 3.4 illustrates the broad steps involved in ML data modelling.

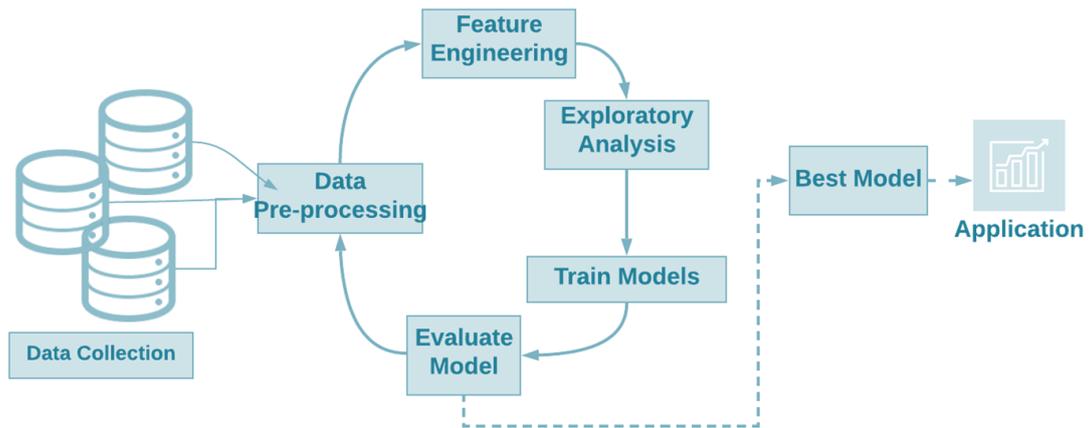


Figure 3.4: Machine learning analytics pipeline

Machine learning algorithms are classified as supervised and unsupervised (Bishop & M., 2006; Tan et al., 2005). Supervised learning has independent attributes as input and dependent attribute as a target (Russell et al., n.d.).

Supervised learning is used to solve the regression and classification problems. For the regression problem, feature attributes are continuous, and for the classification problem, features attributes are categorical. Supervised models performance can be optimized through iterative process and model parameters.

Unsupervised learning models are feed with only independent attributes, and the target is not known. The main task of these models are grouping similar data points, and this method creates its own label (Bishop & M., 2006). Clustering and Classification problems are solved by using unsupervised learning. A broad categorization of supervised and unsupervised learning with algorithms is shown in Figure 3.5.

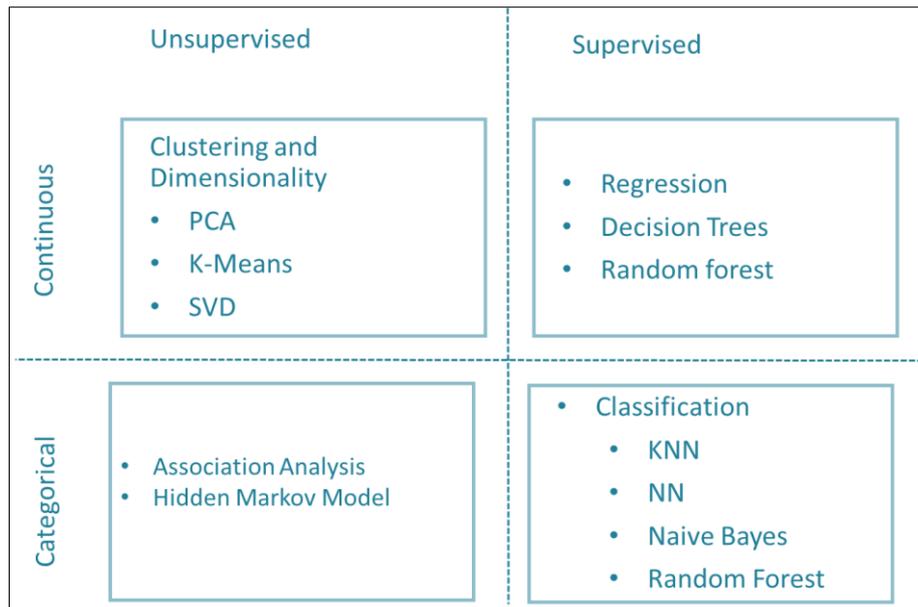


Figure 3.5: Supervised and unsupervised machine learning

Machine learning methods used in this thesis for solving the classification problem are as follows;

3.2.1 kNN – (k-Nearest Neighbors)

kNN is a supervised simplest algorithm and applied in many engineering domains (J. S. Chen et al., 2020; Russell et al., n.d.). Input feature variables in kNN consist of the k closest data points in the feature space and the output is the probability of the class membership (Bröcker et al., n.d.).

kNN, a data point is categorized with the plurality vote of its neighbour data points, i.e. the object will be allocated to the class among its k nearest neighbours (J. S. Chen et al., 2020).

Properties:

- It is considered as “lazy” supervised algorithm because as the model does not have any specialized learning phase and all data are considered for a classification task.
- It also said as Non-parametric algorithm as it doesn’t assume anything about the available data (Tan et al., 2005).

kNN model implementation steps are as follows;

- Feed the data in the model (Train and Test)
- Choose the value of k- closet neighbours
- The algorithm will calculate the distance for each point in the test dataset. The geometric distance can be calculated using Euclidean, Manhattan, Hamming etc. The popular method is the Euclidean distance method.

- The Euclidean function is represented as below;

$$\sqrt{\sum_{i=1}^k (x_i - y_i)^2} \quad (3.9)$$

- The Manhattan function is represented as below;

$$\sum_{i=1}^k |x_i - y_i| \quad (3.10)$$

Where,

x_i, y_i are the two data points in Euclidean space.

- kNN algorithm assigns the class to the data points in the test data.

The illustration of two-class (*Class A & Class B*) classification problem solving by the kNN algorithm is shown in Figure 3.6.

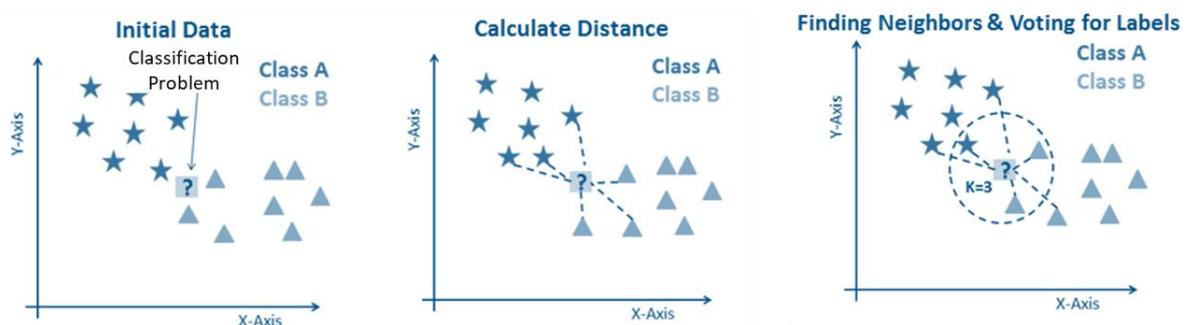


Figure 3.6: kNN method

3.2.2 Naïve Bayes' (NB) classifier

Naïve Bayes' classification algorithm is based on Bayes' theorem, and it assumes that all the features class attributes are independent of each other (Bishop & M., 2006). Bayes' rule's main interest lies in identifying the posterior probability, i.e. the probability of a Label (class) for the feature attributes $P(L | features)$ (Bishop & M., 2006). Bayes' rule can be expressed for class C and features f as ;

$$P(C|f) = \frac{P(C)P(f|C)}{P(f)} \quad (3.11)$$

Where,

$(C | f)$ is the posterior probability of class C .

$P(C)$ is the prior probability of class C .

$(f | C)$ is the likelihood, i.e. probability of predictor given class.

(F) is the predictor prior probability.

The assumption of the NB model is ;

“it is a probabilistic machine learning algorithm built on Bayes' theorem with the 'naïve' assumption of conditional independence between every pair of features given the value of the class variable” (Pedregosa et al., 2011)

Let's consider the class C (target) as y , and features attribute $X = x_1, \dots, x_n$, according to Bayes' rule is defined as follows;

$$P(y | x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots, x_n|y)}{P(x_1, \dots, x_n)} \quad (3.12)$$

On applying the assumption of conditional independence, it can further be written as;

$$P(x_i|y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i|y) \quad (3.13)$$

This further can be simplified for all i as shown below;

$$P(y | x_1, \dots, x_n) = \frac{P(y) \prod_{i=1}^n P(x_i | y)}{P(x_1, \dots, x_n)} \quad (3.14)$$

As $P(x_1, \dots, x_n)$ is constant, and the equation will become;

$$P(y | x_1, \dots, x_n) \propto P(y) \prod_{i=1}^n P(x_i | y) \quad (3.15)$$

$$\hat{y} = \operatorname{argmax}_y P(y) \prod_{i=1}^n P(x_i | y) \quad (3.16)$$

NB is easy to use as it can be implemented easily without parametric hyper tuning. It can effectively handle the large data set.

3.2.3 Random Forest (RF)

Random forest is an ensemble supervised classification algorithm, and it is built on decision multiple decision trees using bootstrapping (Gomes et al., 2017). The model is able to achieve higher accuracy over outliers because it's node is split randomly depends on proximities and OOB (out of the bag) (Gomes et al., 2017).

In Figure 3.7, the generation of a number of decision trees and their branching by taking into account the data input and the RF model parameter tuning is illustrated.

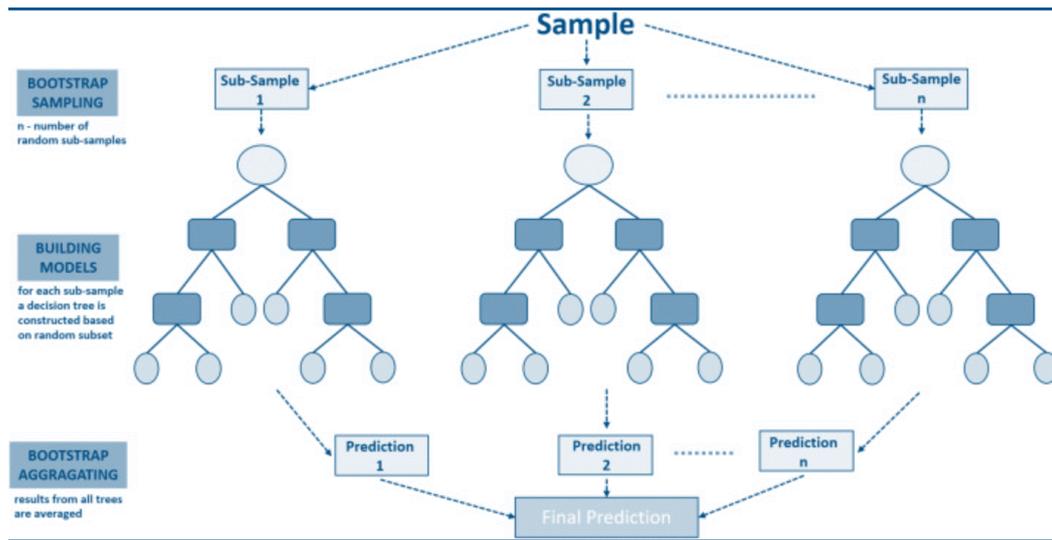


Figure 3.7: RF model formed from multiple decision trees (Crisci et al., 2012)

Overfitting problem in RF can be overcome by building several trees, bootstrapping and splitting the nodes as the best split within a random subset (Breiman, 2001). Hyper-parameters that can be tuned are “number of trees”, “depth of trees”, “the maximum number of features attributes at each split”.

The main benefit of using RF is to avoid overfitting, a problem where decision trees fail to give unbiased results. However, the major disadvantage of this model is interpretability and therefore, it is considered a black-box model.

3.2.4 Neural Network (NN)

Neural network method is influenced by human brain functioning, which is familiar with the patterns (Bishop & M., 2006). A simple single-layer NN, which is also called as “perceptron” is represented in Figure 3.8.

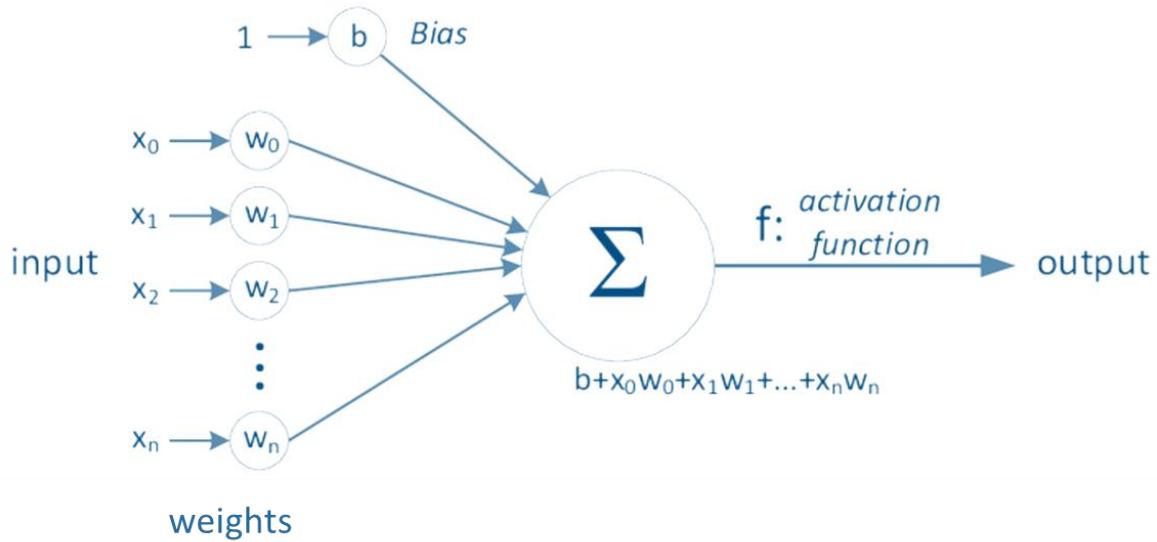


Figure 3.8: Single layer NN

NN consists of an input layer, activation function and output layers; in the above diagram x_1, \dots, x_n are the input feature attributes. Each of the feature attributes is multiplied with weight w_1, \dots, w_n , which represents the strength of nodes. Bias value b helps in moving the activation function low or high.

$$y = x_0w_0 + x_1w_1 + x_2w_2 + \dots + x_nw_n + b \quad (3.17)$$

Where,

y is the target variable

$x_i = x_1, \dots, x_n$ is the input feature attributes

$w_i = w_1, \dots, w_n$ is the weight

Therefore,

$$y = \Phi \sum x_i w_i \quad (3.18)$$

Where Φ is the activation function.

Activation function Φ helps NN to learn complicated things. The main function of it is to convert an input node to an output node. Non-linear activation functions Φ are sigmoidal, hyperbolic, Relu etc. (Bishop & M., 2006; Tan et al., 2005).

A single layer is combined with multiple layers to solve non-linear problems, and it is called as MLP (Multilayer perceptron). MLP is supervised learning, and it uses backpropagation technique for training (Johansson et al., 1991). MLP holds the ability to solve complex classification problems. MLP working flow is shown in Figure 3.9.

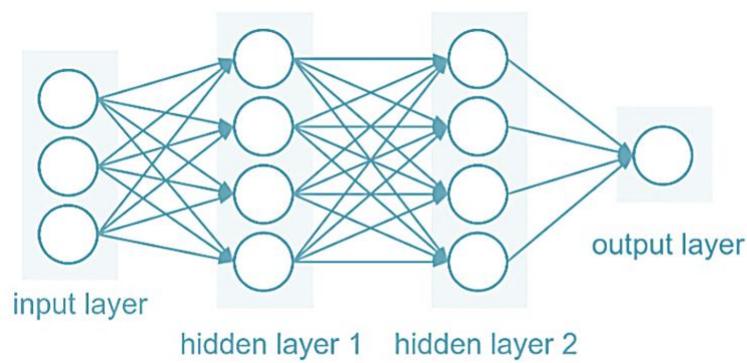


Figure 3.9: Multi-layer NN (Sze et al., 2017)

BPNN (Back-propagation neural network) are gradient descent based approach, it first takes the input values forward followed by error calculation and responds back to previous layers (Johansson et al., 1991). Other refined implementations are BFGS (Broyden-Fletcher-Goldfarb-Shanno) (Møller, 1993), and it uses a ‘hill-climbing’ process for fitting a class that is based on Newton’s method.

Although ML methods are intelligent methods in deriving pattern out of the huge amount of data, they have a few limitations in terms of various optimization and computation related issues. Table 3.5 presents the summary of the strengths and weaknesses of ML methods (Juarez-Orozco et al., 2018; Kuhn & Johnson, 2013)

Table 3.5: Strength and weakness of ML methods

ML Algorithms	Strengths	Weakness
KNN	Intuitive algorithm	The number of neighbors must be determined by the user.
		High computational complexity
NB	Performs well in small datasets where the conditional independent assumption needs to hold.	Assumption of independence among features attributes is required.
RF	They can deal with categorical features (non-linear problems).	No interpretability
	Powerful and accurate	Overfitting can occur easily.
	They work well in data sets with a large number of features.	The number of trees needs to manually selected.
NN	Powerful	The complexity of network structure
	Difficult functions can be modelled.	Time-consuming for large data sets
		Overfitting and weak interpretation

ML supervised classification methods are selected to address RQ2, which is a dynamic garment supplier classification problem. The aim of RQ2 is to predict the best supplier for a newly arriving customer order. This requires the training of ML classification models on the historical order data in order to learn the order allocation patterns and to predict the future supplier allocation for a new order based on the learned patterns. The prediction of a garment supplier for a new customer order constitutes a ML problem; therefore four popular ML classification models were chosen arbitrarily to classify the suppliers based on customer orders. Irrespective of the individual strengths and limits of these methods, the main aim of applying these methods was to investigate their prediction performances based on the customer order data having the supplier information. The sample size of the data was relatively small, which has mostly the categorical variables as described in the Chapter 5.

3.3 Evolutionary optimization algorithms

Evolutionary algorithms are popular for solving optimization and learning problems that are sometimes correlated or independently solved depending on the problem contexts (Xinjie & Mitsuo, 2010). There exists a variety of optimization problems such as multi-objective optimization, combinatorial optimization, and constrained and unconstrained optimization. The major challenge in solving the optimization problem arises from the fact that the complex objective functions are difficult to optimize because of our inability to compute the objective value of the function for each solution in the population. This challenge is addressed by the learning algorithm that intelligently approximates fitness function value from the set of previous solutions in order to build a new set of simpler solutions. This process is known as evolutionary approximation or learning. EAs are a family of such evolutionary learning algorithms that learn from a population of solutions and retain them to be able to evolve into a new generation of solutions (Deb et al., 2002). Therefore, EAs have found many applications in the fields such as AI, OR, and industrial engineering, wherein optimization problems requiring evolutionary approach in the computation of their solutions are focused. Figure 3.10 illustrates the steps involved in the evolution of solutions in EAs.

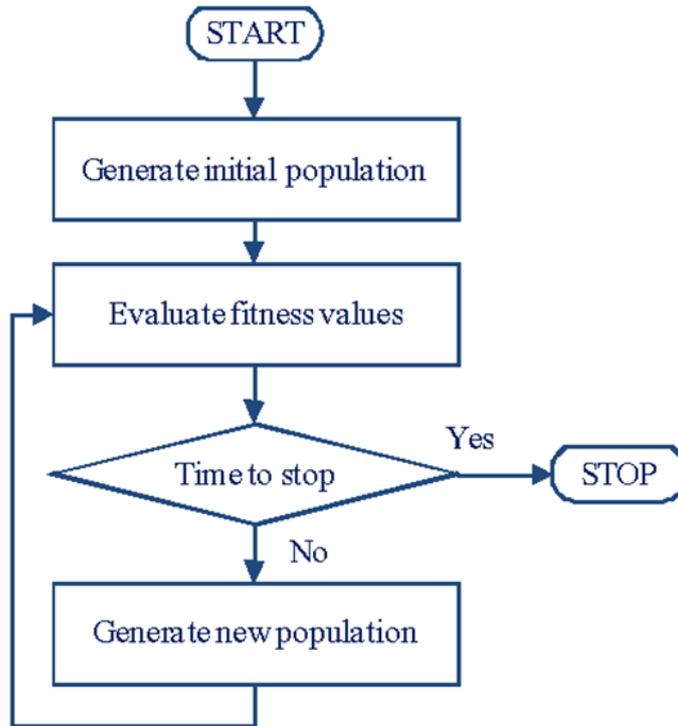


Figure 3.10: Flowchart of EA's steps (Kachitvichyanukul, 2012)

EAs generate solutions for a given optimization problem in an evolutionary manner. Each solution in the population is known as an individual that is represented in terms of gene codes, and its performance is measured using the computed fitness value. Since EAs select fittest individuals, their convergence relies on the fittest individuals in the population. Secondly, since each individual undergoes genetic evolution by means of a multitude of varied operations, thereby expanding the solution space, EAs are considered to be variation-driven (Blickle & Thiele, 1996). Owing to the EAs' learning power, they constitute one of the basic elements of computational intelligence (Fortin et al., 2012).

If the optimization problems at hand are complex and hard to solve, then the guaranteed global optimal solution may lie beyond the horizon of solution search space and affordable time frame. Several heuristic algorithms, especially GAs that are highly problem-dependent algorithms, are developed and proposed by the researchers to overcome the limitations of EAs

in terms of quickly finding a good quality solution; however, they too suffer the limitation as the optimality of the final solutions cannot be guaranteed and the number of generation required to arrive at the final better solution cannot be determined (Xhafa & Abraham, 2010).

3.3.1 Genetic algorithm (GA)

Genetic algorithm is one of the most popular classical EAs that generate random search solution space using metaheuristic learning approach. GA is a search heuristic method that mimics the process of natural evolution (Horn et al., 1994), and (Deb et al., 2002). In a GA method, chromosomes are a population of strings, in which the candidate solutions are encoded (population individuals) in order to solve an optimization problem. Genetic Algorithm (GA) is a highly flexible tool for setting and modifying the objectives. GA is an evolutionary method in the sense that it evolves towards better solutions. The evolution of GA usually begins with an initial population of randomly formed individuals, and then it results in multiple generations. In every generation, the fitness of every individual in the population is evaluated using fitness function, on the basis of which the multiple individuals from the initial population are chosen, and subjected to crossover and mutation (recombined and randomly mutated) to generate a new population (Maier et al., 2019).

As GAs embody natural selection in their genetic evolution, individuals in the population, being the solutions for the optimization problems, are evaluated using a fitness function. For each individual i with the fitness value f_i in the population comprised of n individuals (population size = n), the relative fitness value of each individual is given by Eq. 3.19.

$$p_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (3.19)$$

In the subsequent iterations, the newly generated population is used. The quality of the individuals improves in each generation over the iterations. Once a maximum number of

generations are generated, iterations can be terminated or can be continued until a satisfactory fitness level for each individual has been met. The following steps are included in the implementation of the GA method.

- Step 1: Initialization of the population of chromosomes
- Step 2: Evaluation of each chromosome with the help of fitness function
- Step 3: Crossover: a selection of parents according to their fitness values and creation of new offspring chromosomes
- Step 4: Random mutations of the chromosomes
- Step 5: Elitist selection: retain the set of fittest chromosomes from the previous generation and the new ones from Steps 3 and 4 results
- Step 6: Repetition of Steps 2 to 5 till termination criteria are met

The synthesis of strengths and weakness of GA have been illustrated by many researchers, for example, (Goldberg, 1989; Sette & Boullart, 2001) – and presented in Table 3.6

Table 3.6: Strength and weakness of GA method

Strength	Weakness
Concepts are straightforward to understand and implement.	Tuning can be challenging and difficult to get global optimum solutions.
Genetic algorithms are inherently parallel. In other words, it performs a similar search in multiple regions of the solution space.	Long computational time.
The solution improves over time.	

As we process the customer order data along with the supplier data, as presented in Chapter 6, for the dynamic assignment of the orders to the best suppliers, which is RQ3, GA and GA-TOPSIS methods are selected because of their ability to give approximately realistic and optimal solution for the decision scenarios formed specifically to address the RQ3, as illustrated in Chapter 6. GAs have the unique ability to improve the solutions over the

generations and explore the local solution space. However, it is not certain to produce global optimal solutions using GA-based heuristic methods.

3.4 Summary

The methods presented in this chapter are applied based on their significance for the decision problems that the research questions formulated in this thesis aim to address. These methods are applied to the data collected from different sources, such as decision-makers' judgement data used for the RQ1; real industrial product sales data for the RQ2; and simulated data for the RQ3. The data used in this thesis are collected in accordance with the requirements and context of the research questions introduced in Section 1.2. Moreover, the general strengths and weaknesses of the applied methods are discussed.

The MCDM methods: AHP, TOPSIS and Fuzzy-TOPSIS are applied to address the RQ1 because of their unique ability to process decision makers' evaluation data for criteria and suppliers. Identification of the most important raw material supplier selection criteria is a complex MCDM problem, for which the AHP method is suitable as it produces realistically analytical solution. The TOPIS method is used for the evaluation of raw material suppliers as it can set the objectives of the decision maker in terms of criteria weights computed using the AHP method. Furthermore, the Fuzzy-TOPSIS method is chosen in the decision scenario comprised of multiple criteria, suppliers and decision makers. The Fuzzy-TOPSIS method addresses the uncertainty arising from the conflicting and ambiguous judgements of the multiple decision makers.

ML classification methods are selected to solve the supplier prediction problem formulated as RQ2. ML methods are highly efficient learning algorithms that derive learning patterns from the historical data. In the context of RQ2, the historical customer order data is used to train popular ML classification algorithms; kNN, Naïve Bayes, RF and NN. These are highly

efficient learners, but follow different rules for deriving knowledge from the data. Therefore, they are selected to investigate and analyze their performance on the data used to address RQ2.

The metaheuristic GA method is used to solve RQ3, i.e. to dynamic assignment of customer orders to the best garment suppliers. The GA method is suitable to the problem specified in RQ3 given its unique ability to produce optimal solutions for the defined objectives in an evolutionary and iterative manner. The GA method is chosen to solve the small-series fashion retailers' objectives while allocating new batch of customer order to the best matching garment supplier with their objectives.

Overall, the methodological approach followed in this thesis is experimental and is selected from the point of view of novel decision problems of the small-series fashion industry, the identified gaps in the existing literature, as highlighted in the literature review, and also from the standpoint of the challenging research problems that are formulated as the research questions. In this thesis, the problem of sourcing mechanism within the small-series fashion industry, both for the raw material and finished garments is developed using the primary data and the mixed, exploratory and experimental methodological approach. The formulated research questions in this thesis are unique and highly relevant to the current requirements and challenges faced by the small-series fashion industry, therefore, this thesis contributes to solving key SCM decision problems.

Chapter 4

Static supplier selection for the raw materials in small-series fashion production

In this chapter, the first research question (see Chapter 1) RQ1, i.e. how to select raw material suppliers for the production of small-series fashion products is addressed using MCDM methods. The main objective of this chapter is to develop a mechanism for the small-series fashion retailers in order to be able to identify key decision factors in terms of criteria that align with their business objectives and thereby to enable them to optimally select best suitable suppliers for the reliable and efficient sourcing partnership. As discussed previously in Chapter 1, the RQ 1, addressed in this thesis, is a static decision problem in the sense that the frequency with which the decision to find suitable raw material suppliers is low and vary as per the discretion and the needs of retailers.

In a small-series fashion SCM and production system, where individual consumer level customization is emphasized, the development of robust production and supply chain network and configuration strategies is a complex and challenging process (Macchion et al., 2015). Reliable and potential suppliers are the backbones and major drivers of companies' overall business success. In order for the companies to survive in the fierce market competition, it is indispensable to choose suppliers in an effective, efficient and profitable way. Short product life cycle, rapidly changing fashion trends, and ever-changing consumer preferences drive the fashion industry to the point that it becomes highly challenging and difficult for them to make effective procurement decisions. Fashion companies not only need to ensure that they have the best suppliers but also to evaluate their performance from time to time based on various performance indicators. Moreover, textile companies are constantly required to comply with various environmental and market regulations owing to which the number of criteria for the

supplier selection varies. More often than not, these criteria are complex in terms of their relationship with one another and their relative importance.

The fashion industry is undergoing significant transformation in recent years given the global competition and emergence of new markets. In addition to it, knowledge of consumer choices is, more than ever, becoming critical for the development and growth of the fashion industry as a whole. Supplier selection and supply chain performance evaluation in the fashion industry is an integral part of its business operations and is a complex process as it involves careful analysis of a number of key criteria. All these factors constitute a multi-criteria decision making problem of supplier selection as the part of supply chain management in the small-series fashion industry (J. L. Yang et al., 2008). Many studies point out that the key to surviving in the fierce market competition is by effectively being more adaptive and flexible to adjust to the changing consumer preferences (Lesisa et al., 2018).

In recent years, there has been an incessant growth of advanced researches and innovations in information technology, which has paved the way for many possibilities than it was possible a few decades ago. Decision making in the context of small-series fashion industry must be done in a real-time given the rapid changes in the market trends. To make this possible, supply chain managers need to have access to useful information from customers' and the supplier's side. Companies' advanced big data analytics integrated with their information management systems allow their managers to gauge the market situation and to identify important factors for making decisions, including supplier selection (Banica & Hagi, 2016). As a result, fashion retailers are now able to tap into their data repositories to derive significant insights about the consumers in order to develop supply chain strategies that will enable them to quickly adapt and respond to the market forces.

Multi-criteria decision methods (MCDM) are widely popular and used for solving supplier selection problems as they can address the conflict between selected criteria and map their relative importance (Kahraman et al., 2015). However, conventional criteria and methodologies used for solving supplier selection problems do not perform well given the rapid transformation of the fashion industry due to changing consumer behaviour, data-driven business models, and digital market trends.

In this chapter, our main objective is to identify new criteria relevant to digital fashion business models and use them in MCDM methods for selecting the best suppliers. In this study, the focus of the supplier selection problem can be located in a small-series fashion SCM and production framework. Through a literature study, potential criteria are identified and expert opinions about their relevance for the supplier selection in an e-commerce business framework.

4.1 State-of-the-art

Supplier selection entails four major stages: 1) choosing a subcontracting method, 2) preliminary screening of possibly suitable suppliers based on various important criteria, 3) ranking of suppliers, 4) selection of best suppliers (Weele, 2010). Detailed descriptive analysis of stepwise processes involved in the supplier selection in various industries is presented in the study of (Taherdoost & Brard, 2019). The plethora of methods including optimization methods have been developed and presented in various studies (e.g., Teng & Jaramillo, 2005; Liu, Quan, Li, & Wang, 2019; Chai & Ngai, 2015) to address supplier selection problems taking into account various criteria. (Yildiz, 2016) applied interval type-2 Fuzzy-TOPSIS and Fuzzy-TOPSIS methods to select the best supplier among available alternatives of garment suppliers for the Turkish fashion company. However, there is a

significant dearth of literature addressing supplier selection problem using MCDM methods with the main focus on the small-series fashion industry.

Several studies have explored the problem of supplier selection based on multiple qualitative and quantitative criteria, for example, (Liao & Kao, 2010; Ku, Chang, & Ho, 2010). A detailed study on various criteria not only from economic aspect but also from environmental and social aspects to be included in supplier evaluation analysis can be referred in (Vieira, de Godoy Lima, & Gehlen, 2016; Winter & Lasch, 2016). However, the criteria based on which multi-criteria decision methods applied are traditional ones and do not reflect the changes in the fashion industry due to the advent of advanced digital technology and rapidly varying customer preferences.

4.1.1 Multi-criteria decision methods (MCDM) for supplier selection

An integrated model combining the Analytic Hierarchy Process (AHP) and linear physical programming (LPP) model together to select suppliers is presented in the study by (kumar et al., 2018). A highly efficient hybrid supplier selection model based on Data Envelopment Analysis (DEA), a mathematical programming based method, is presented by (Alikhani et al., 2019), which incorporated both desirable and undesirable criteria defined as risk factors and the results from this study indicate that the separate analysis of suppliers based only on defined subjective risk criteria other than quantitative information is not effective and leads to wrong decisions. Another interesting study by (Guarnieri & Trojan, 2019) employed Copeland method, which computes aggregated criteria weights; AHP method to calculate individual criteria weights; and ELECTRE-TRI method for sorting suppliers based on social, ethical and environmental criteria. Using a broad supplier selection framework, new methods that have not been applied in traditional supply chains along with the methods used for all the phases of supplier selection in a range of industries are presented in the form of detailed

literature review by (de Boer et al., 2001). (Chai et al., 2013) presented a systematic review of the vast literature on multi-criteria decision approaches applied for supplier selection problems in different industries and classified these approaches into seven broad categories based on various uncertainties and risk factors.

In the age of digital business models, fashion companies are striving to take advantage of emerging big data tools and technology to improve their business performance and growth. In the context of small-series fashion production, problems arising out of uncertainties in supply chain network configuration and an increasing degree of changes in consumer preferences lead to the need of addressing a supplier selection problem based on strategic partnership goals and exploring new relevant factors that can drive effective sourcing decision making. Modern information processing technology enables fashion companies to identify the factors that drive consumer shopping patterns and also market dynamics. There is a significant dearth of literature that addresses these new developments in the fashion industry.

4.2 Methodology

Supplier selection, in general, entails two main steps: firstly, to identify the potential criteria based on which best suppliers to be chosen for the sourcing, and secondly, to apply MCDM methods to classify and rank the suppliers from which the top-ranked suppliers can be selected for making the business deals.

A detailed literature review of various multi-criteria decision making (MCDM) methods has been presented in (Ho et al., 2010). This review presents individual methods, such as Data Envelopment Analysis (DEA), Mathematical programming, AHP, Case-based reasoning, ANP, Fuzzy Set Theory, Simple multi-attribute rating technique, and Genetic algorithm, and several hybrid approaches that have been prevalently used in supplier evaluation and selection, and discusses in detail the prevalent criteria for supplier evaluation and also the

limitations of the MCDM methods. The major limitation that the study found in this study is that the criteria selected for supplier evaluation and selection did not have any influence on companies' business strategies and goals. With the changing business frameworks and digital technology, it has been indispensable for the decision-makers to incorporate those criteria which have the strong influence of companies' business goals, which is the main focus of our study.

This study is aimed at filling a lacuna in the study of raw material supplier selection in the context of small-series apparel production. One of the key objectives in this study is to identify important criteria, both quantitative and qualitative, from the point of view of sourcing managers working in fashion industries.

In the first step, questionnaire-based survey approach, in line with (Dickson, 1966 and Weber, Current, & Benton, 1991), is adopted to derive opinions and consensus from supply chain experts and managers from four European fashion companies on most important supplier selection criteria from the perspective of new emerging digital fashion business models. The formulated questionnaire aimed at helping managers to evaluate the relative importance of relevant supplier selection criteria with respect to each other.

For the second step, MCDM models viz., AHP; TOPSIS; Fuzzy-TOPSIS models are implemented. AHP is one of the widely applied methods for solving relative measurement problems. However, its popularity is due to its ability to compare the relative performance of actions or alternatives to be evaluated based on evaluation criteria. AHP method was introduced by (Saaty, 1977), and it has been applied to solve a plethora of complex MCDM problems ever since. Therefore, I applied the AHP method for computing supplier selection criteria weights.

The choice of TOPSIS, Fuzzy-TOPSIS methods is corroborated by the fact that these models are developed using the foundations of fuzzy set theory (Zadeh, 1965; Zadeh, 1973), and they possess unique ability to handle fuzzy human judgements or decisions involved in MCDM problems. In this study, industry experts' judgements on important criteria for supplier selection and also on the evaluation of suppliers based on these criteria have been used as an input. These judgements are highly likely to suffer from vagueness in terms of making a relative evaluation. Therefore, the selection of the aforementioned methods is justified. Moreover, these methods are well capable of aggregating multiple decision-makers' evaluation of alternatives and ranking them based on computed scores.

There is a vast literature (see for Ex., Munier, Hontoria, & Jiménez-Sáez, 2019; Zavadskas, Turskis, & Kildienė, 2014) available that outlines the theoretical and mathematical formulations of all MCDM methods including those applied in this study. The detailed theoretical and mathematical formulations for the chosen MCDM methods are presented in Chapter 3.

4.3 Experimental results

The obtained experimental results are described in the following sections step by step.

4.3.1 Selection of raw material supplier selection criteria

In order to select highly relevant criteria from the strategic point of view of current market and customer trends and digital technology for fashion supplier selection, inputs from the decision-makers comprised of sourcing managers from four European fashion companies are collected. In a face-to-face survey, two supply chain experts from each of the four e-commerce fashion companies were involved. These companies specialize in small-series customized products such as customized shirts, women bags, all-season multi-functional jackets and customized luggage trollies. From the perspective of data ethics principle, the

respondents were anonymized. In total, eight respondents were involved in the survey. The main question that was incorporated in the survey questionnaire is: What are the most important criteria, from the perspective of your current business strategies and goals, and digital fashion supply chain that you use for selecting your suppliers? The respondents were presented with the list of fifteen criteria as shown in Table 4.1, that are preselected based on our literature study, and they were asked to select those that they consider highly important for their business strategies, needs and goals. Respondents were asked to select all those criteria from the list of fifteen criteria that they feel important for them in order for making a decision in regard to supplier selection.

The respondents were asked to rank the criteria based on their importance on the scale of 1-15: '1' signifying the most important, and '15' signifying the least important. In order to randomly select top important criteria of the list, the mean score of all the numbers assigned by respondents to each of the criteria is used. As a result, mean values for all the criteria considered for evaluation using a ranking number assigned by the expert respondents are computed and are given in Table 4.1.

Table 4.1: Illustration of mean value computation for supplier selection criteria

	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>	<i>C6</i>	<i>C7</i>	<i>C8</i>	<i>C9</i>	<i>C10</i>	<i>C11</i>	<i>C12</i>	<i>C13</i>	<i>C14</i>	<i>C15</i>
Respondent 1	1	12	13	11	9	10	4	5	3	2	6	7	15	8	14
Respondent 2	1	11	12	14	10	9	2	3	6	4	8	13	7	15	5
Respondent 3	3	7	6	8	15	14	2	5	4	1	9	10	11	12	13
Respondent 4	2	5	12	11	15	13	3	4	7	6	8	1	10	14	9
Respondent 5	1	12	10	15	13	11	3	4	2	5	6	14	7	9	8
Respondent 6	1	13	15	14	10	11	6	3	5	7	4	2	9	8	12
Respondent 7	1	7	15	14	12	10	5	4	8	9	2	6	3	13	11
Respondent 8	1	14	13	15	12	10	4	3	2	8	5	6	11	9	7
Mean	1.3	10.1	11.8	12.7	11.9	11	3.6	3.8	4.6	5.25	6	7.37	9.12	11	9.87

Consequently, the top nine criteria were selected to be evaluated using the AHP method based on the smallest average ranking number, as can be observed in Figure 4.1. The criterion (for ex. Cost) having the smallest mean value of all the numbers assigned by respondents is selected as the first most important criteria in the list of nine criteria. Likewise, the criterion

(for ex. Sustainability) with ninth-lowest mean value is selected as the ninth most important criteria in the list. The description of all the criteria and their selection as per the smallest computed mean value of the ranking score is given in Table 4.2.

Table 4.2: Evaluation score of supplier selection criteria

<i>Criterion (C)</i>	<i>Type</i>	<i>Evaluation score</i>	<i>Selected?</i>
Cost (C1)	Quantitative	1.3	YES
Market reputation(C2)	Qualitative	10.1	NO
Service efficiency(C3)	Qualitative	11.8	NO
Management efficiency (C4)	Qualitative	12.7	NO
R&D facilities(C5)	Qualitative	11.9	NO
Late delivery(C6)	Qualitative	11	NO
Lead time (C7)	Quantitative	3.6	YES
Quality (C8)	Qualitative	3.8	YES
Flexibility (C9)	Qualitative	4.6	YES
Operational efficiency (C10)	Quantitative	5.25	YES
Innovation (C11)	Qualitative	6	YES
Trust (C12)	Qualitative	7.37	YES
Location (C13)	Qualitative	9.12	YES
Digitization (C14)	Qualitative	11	NO
Sustainability(C15)	Qualitative	9.87	YES

The distribution of mean values of all criteria ranking numbers assigned by the respondents is illustrated in Figure 4.1.

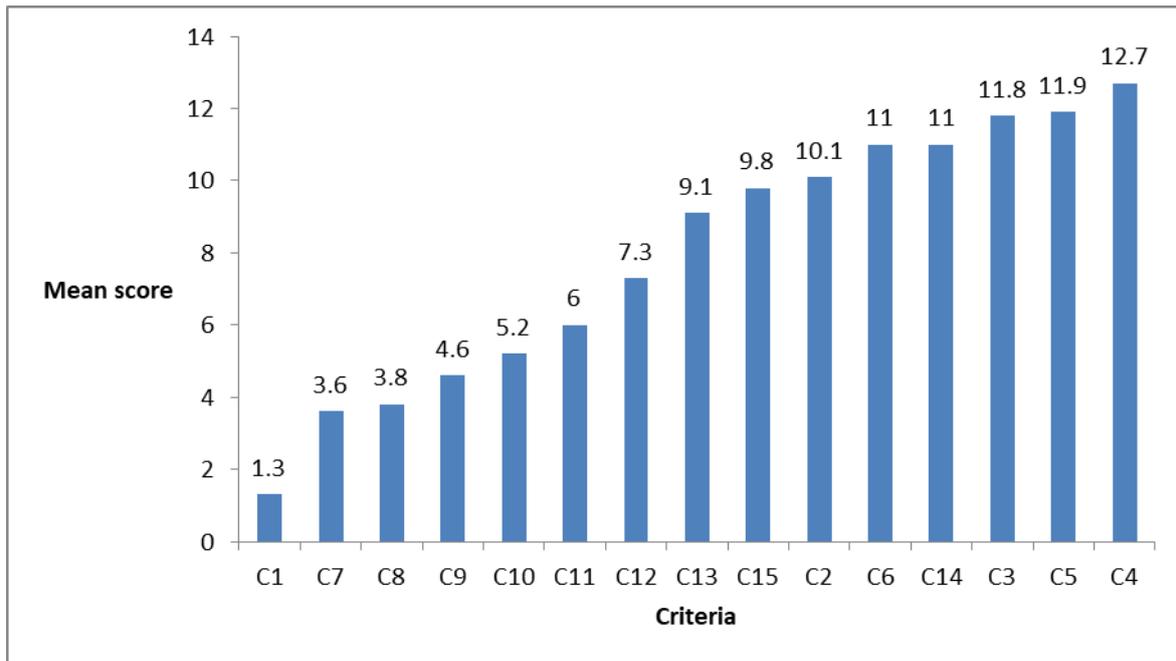


Figure 4.1: Ranking of criteria based on the mean value of evaluation score

4.3.1.1 AHP for criteria ranking

In the next step, the relative importance of the nine supplier selection criteria is computed using the AHP method, which is widely used for solving multi-criteria decision making in various industries (Vaidya & Kumar, 2006). As the first step in criteria evaluation, one of the industry experts is asked to evaluate the relative importance of these criteria with respect to each other keeping their business strategies and the main goal of selecting best suppliers in mind. For the inputs of evaluation, the questionnaire is prepared (as shown in Appendix II) in which respondents are asked to fill the pairwise comparison matrix using the linguistic scale, presented below in Table 4.3, proposed by (Saaty, 1977) that has previously been used in many studies.

Table 4.3: Saaty’s pairwise comparison scale

Linguistic description	Numerical value
Equally important	1
Moderately important	3
Strongly important	5
Very strongly important	7
Extremely important	9

Evaluation of supplier selection criteria, given in Table 1, by one of the industry experts constituted pairwise comparison matrix (PCM) as shown in Table 4.4, which then checked for consistency as per the AHP steps explained in the Section 3.1.1 of Chapter 3.

Table 4.4: Pairwise comparison matrix for criteria evaluation

	Cost	Lead Time	Quality	Flexibility	Operational efficiency	Innovation	Trust	Location	Sustainable Operations
Cost	1	1	7	7	5	7	7	9	5
Lead Time	1	1	5	7	5	3	5	7	5
Quality	1/7	1/5	1	7	7	5	9	9	5
Flexibility	1/7	1/7	1/7	1	5	3	5	3	5
Operational efficiency	1/5	1/5	1/7	1/5	1	3	5	3	5
Innovation	1/7	1/3	1/5	1/3	1/3	1	7	7	5
Trust	1/7	1/5	1/9	1/5	01/5	1/7	1	7	5
Location	1/9	1/7	1/9	1/3	1/3	1/7	1/7	1	3
Sustainable Operations	1/5	1/5	1/5	1/5	1/5	1/5	1/5	1/3	1

Finally, the priority vectors of criteria are computed, values of which are the normalized values of PCM calculated by geometric mean method, which is one of the many normalization methods used for priority vector calculation (Saaty, 1990). The computed score of criteria is given in Table 4.5. The scores computed as the priority score are represented in terms of percentage points: for Ex., the priority score for the criteria *Cost* is 0.27, and it can be

interpreted as the 27% weightage in terms of importance. The range of priority score is from 0 to 1.

Table 4.5: Computed criteria weights

Criteria	Weights
Cost	0.27
Lead Time	0.22
Quality	0.17
Flexibility	0.08
Operational efficiency	0.07
Innovation	0.07
Trust	0.04
Location	0.02
Sustainable Operations	0.02

Based on the computed priority scores, the criteria are ranked, as shown in Figure 4.2. From Figure 4.2, it can be inferred that the top three most important supplier selection criteria are: Cost; Lead time; and Quality.

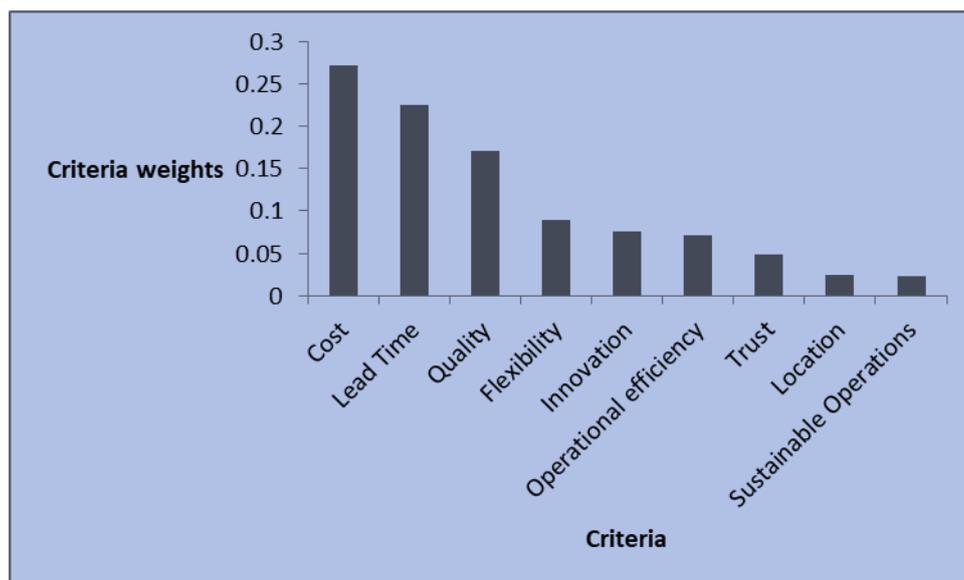


Figure 4.2: AHP ranking of supplier selection criteria

4.3.1.2 TOPSIS method for supplier ranking (A single expert decision)

Based on the criteria evaluation by AHP, TOPSIS method is applied to evaluate suppliers corresponding to each criterion. For the analysis, ten raw material suppliers for small-series fashion production are considered as denoted by Supplier A, Supplier B,....., Supplier J alphabetically. The candidate suppliers are located in the European zone, and they provide raw materials such as fabrics and other accessories, and customization services for the customized products, as mentioned in Section 4.1, sold by a small-series fashion retail company. For this method, a fashion retail brand is considered, which provides customized shirts to its customers. For the retailer selling customized shirts, suppliers will provide fabric, fabric cutting, stitching, customized operations on shirts, etc. Only one expert is involved in the process of evaluation for ranking suppliers. The decision matrix, including criteria scores calculated by AHP, from Table 4.5, and the evaluation made by one industry expert is shown in Figure 4.3.

	Cost (Euro/m)	Lead Time(days)	Quality	Flexibility	Operational efficiency	Innovation	Trust	Location	Sustainability
AHP Criteria Weights	0.27	0.22	0.2	0.09	0.07	0.08	0.05	0.02	0.02
Supplier A	15	7	5	5	7	3	1	5	4
Supplier B	10	6	4	1	7	5	6	7	2
Supplier C	11	10	2	1	1	1	6	1	4
Supplier D	14	12	2	6	1	7	4	2	3
Supplier E	9	9	1	7	5	7	7	3	1
Supplier F	13	5	7	5	4	6	4	3	7
Supplier G	14	3	6	6	2	4	7	6	7
Supplier H	15	10	2	6	3	2	2	7	2
Supplier I	12	12	3	2	3	4	1	5	5
Supplier J	11	16	7	7	6	5	1	5	6

Figure 4.3: Decision matrix for TOPSIS

In the decision matrix shown in Figure 4.3, values in the first two columns, i.e., Cost (Euro/meter) and Lead Time (days) are the simulated data points, while values in rest of the columns are the evaluation inputs by industry expert using Likert scale as shown in Table 4.6.

Table 4.6: Likert Scale

Linguistic description	Numerical value
Worst	1
Good	3
Better	5
Best	7

The alternative evaluation inputs are collected in a face-to-face interview with the supply chain manager who was asked to fill the empty decision matrix given in the questionnaire. Based on the results from intermediate steps, which include weighted normalization of TOPSIS decision matrix, computation of Ideal scores (positively ideal solutions) and Anti-ideal scores (negatively ideal solutions), and finally, the computation of closeness coefficient values based on which, ten suppliers are ranked as shown in Figure 4. 4.

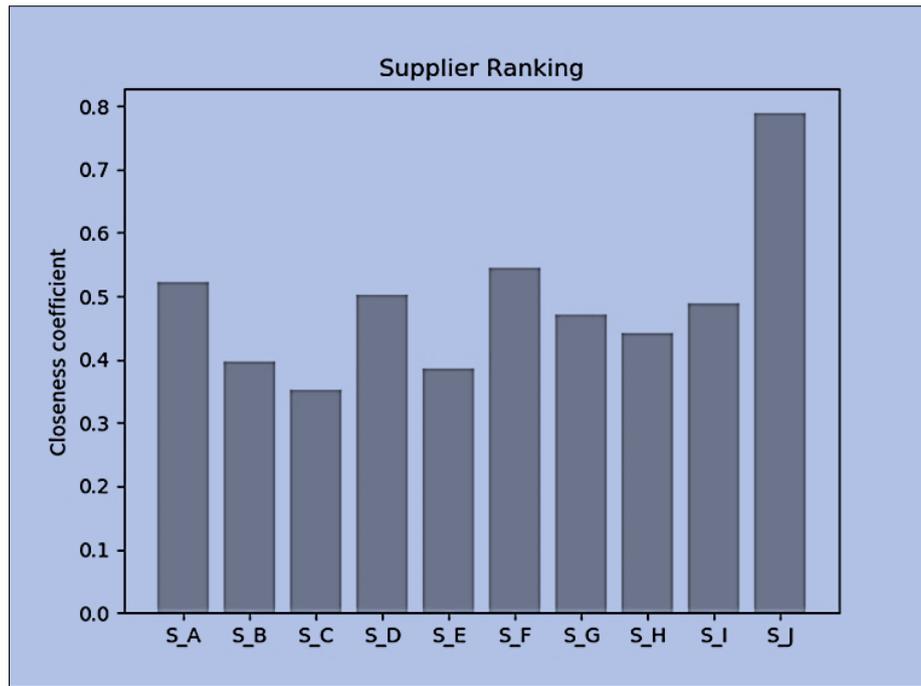


Figure 4.4: Supplier ranking by TOPSIS method

4.3.1.3 Fuzzy-TOPSIS method for supplier ranking (Group decision making)

The results from the TOPSIS method are based on a single expert evaluation. As a further step, group decision making using Fuzzy-TOPSIS method is carried out by involving four industry experts' evaluation of the same suppliers that were evaluated using the TOPSIS method. As the evaluation of multiple experts is often vague and laden with too much subjective information, Fuzzy-TOPSIS method is applied, which draws from fuzzy number set theory. For the analysis, Triangular Fuzzy Numbers (TFN) are employed, which are widely used for group decision making. The significance of the Fuzzy-TOPSIS method for the group decision making is highlighted by the fact that it is developed as one of the extensions of the Fuzzy-MCDM methods to overcome the limitations of TOPSIS method in terms of handling decision problems under fuzzy environments. Fuzzy-TOPSIS method is specifically the most appropriate approach for the group MCDM problem as it is drawn from the Fuzzy set theory that contributes to transforming a fuzzy subset of decision-makers' judgements and evaluations with suitable membership functions (Leekwijck, 1999).

The results from each intermediate step of Fuzzy-TOPSIS method are computed. The steps are detailed in Chapter 3, wherein mathematical formulation of all the steps in Fuzzy-TOPSIS method is presented.

In the first step of implementation of Fuzzy-TOPSIS, group of four industry experts evaluate supplier selection criteria using linguistic variables that are transformed into fuzzy TFN evaluation scale (0-1 range), which is shown in Table 4.7. The step size for the *least to most* and *most to the largest* value in the TFN (Q. Li et al., 1996) is 0.1, which is used to represents the importance weight of criteria in a percentage term.

Table 4.7: Linguistic scale for criteria evaluation

Linguistic description	Triangular Fuzzy numbers
Very low	(0, 0, 0.1)
Low	(0, 0.1, 0.3)
Medium low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
Medium high	(0.5, 0.7, 0.9)
High	(0.7, 0.9, 1.0)
Very High	(0.9, 1.0, 1.0)

The decision matrix for the criteria evaluation by four experts group is shown below in Figure 4.5. The four experts as decision-makers are denoted by DM1, DM2, DM3, and DM4 respectively. The evaluation values in terms of TFN (Triangular Fuzzy Numbers) made by decision-makers in the Fuzzy decision matrix are inputted as given in Table 4.8.

	DM1	DM2	DM3	DM4
Cost	(0, 0, 0.1)	(0.5, 0.7, 0.9)	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)
Lead Time	(0.7, 0.9, 1.0)	(0.9, 1.0, 1.0)	(0, 0, 0.1)	(0.1, 0.3, 0.5)
Quality	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)	(0.7, 0.9, 1.0)	(0.1, 0.3, 0.5)
Flexibility	(0, 0.1, 0.3)	(0.7, 0.9, 1.0)	(0, 0, 0.1)	(0.5, 0.7, 0.9)
Operational efficiency	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0, 0, 0.1)	(0.9, 1.0, 1.0)
Innovation	(0, 0.1, 0.3)	(0.9, 1.0, 1.0)	(0.3, 0.5, 0.7)	(0, 0.1, 0.3)
Trust	(0.9, 1.0, 1.0)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Location	(0, 0.1, 0.3)	(0, 0, 0.1)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)
Sustainable Operations	(0.5, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)

Figure 4.5: Decision matrix for criteria evaluation

In the second step, similar to criteria evaluation, decision-makers are asked to evaluate the same ten suppliers based on each criterion. For the supplier rating, fuzzy rating scale (1-10 range) is used and is shown in Table 4.8. Here, the step size in TFN is 1, indicating the progression of the rating of each supplier on a 1-10 scale. An example of the decision matrix from the experts' evaluation for the criteria 'Cost' in terms of TFN is shown in Figure 4.5. Since nine supplier selection criteria are selected, nine decision matrices similar to the one shown in Figure 4.5, are formed and fed to the Fuzzy-TOPSIS model.

Table 4.8: Linguistic scale for supplier rating

Linguistic description	Triangular Fuzzy numbers
Very low	(0, 0, 1)
Low	(0, 1, 3)
Medium low	(1, 3, 5)
Medium	(3, 5, 7)
Medium high	(5, 7, 9)
High	(7, 9, 10)
Very High	(9, 10, 10)

The decision matrix for the supplier rating for criteria 'Cost' is depicted in Figure 4.5.

	DM1	DM2	DM3	DM4
Supplier A	(9, 10, 10)	(7, 9, 10)	(5, 7, 9)	(0, 1, 3)
Supplier B	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(0, 0, 1)
Supplier C	(0, 1, 3)	(0, 1, 3)	(1, 3, 5)	(3, 5, 7)
Supplier D	(7, 9, 10)	(9, 10, 10)	(1, 3, 5)	(0, 1, 3)
Supplier E	(0, 1, 3)	(9, 10, 10)	(7, 9, 10)	(5, 7, 9)
Supplier F	(0, 1, 3)	(9, 10, 10)	(1, 3, 5)	(1, 3, 5)
Supplier G	(1, 3, 5)	(9, 10, 10)	(5, 7, 9)	(1, 3, 5)
Supplier H	(1, 3, 5)	(9, 10, 10)	(7, 9, 10)	(9, 10, 10)
Supplier I	(0, 0, 1)	(9, 10, 10)	(5, 7, 9)	(0, 1, 3)
Supplier J	(5, 7, 9)	(1, 3, 5)	(7, 9, 10)	(1, 3, 5)

Figure 4.6: Example of a decision matrix for supplier rating for ‘Cost’ criteria

The intermediate steps entailed in the implementation of Fuzzy-TOPSIS are: aggregation of criteria weights; computation of fuzzy weighted normalized decision matrix for supplier rating; and computation of Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS); computation of distance of each supplier from FPIS and FNIS; and finally, the computation of close-ness coefficient of each supplier. Based on the final computation of close-ness coefficient values, all the ten suppliers are ranked, as shown in Figure 4.7.

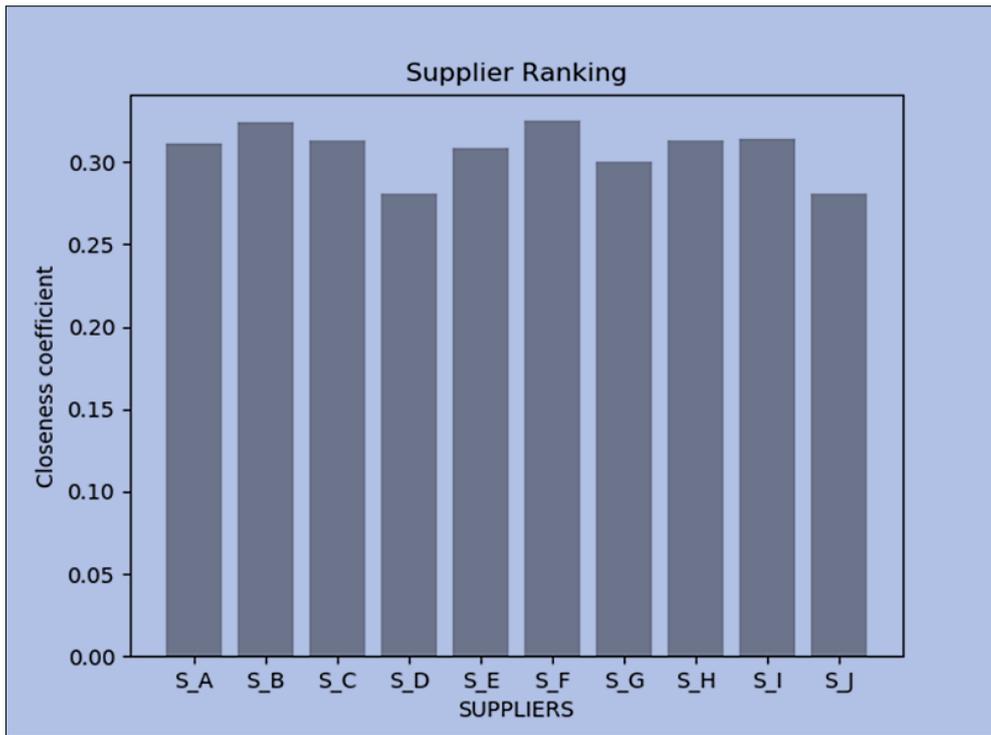


Figure 4.7: Supplier ranking by Fuzzy-TOPSIS method

On comparison of the supplier ranking from Fuzzy-TOPSIS with TOPSIS supplier ranking, it indicates that the ranking for single expert evaluation differs significantly from the group decision making. The top three best suppliers from TOPSIS method are *Supplier J*; *Supplier F*; and *Supplier A*, while from the Fuzzy-TOPSIS method, the top three best suppliers are *Supplier F*; *Supplier B*; and *Supplier C*. Moreover, the three worst suppliers from TOPSIS method are *Supplier C*; *Supplier E*; and *Supplier B*, while from the Fuzzy-TOPSIS method, the top three best suppliers are *Supplier D*; *Supplier J*; and *Supplier G*. This significant variation in the supplier ranking by TOPSIS and Fuzzy-TOPSIS methods can be attributed to the fact that only one decision-maker is involved in the supplier evaluation by TOPSIS method while four experts are involved in the supplier evaluation by Fuzzy-TOPSIS method. Moreover, the fundamental difference could be due to the different normalization method that each of these two methods involves. It is in line with the established findings in the area of

MCDM methods that found the variation in the results drawn from each MCDM method. Furthermore, the ranking of suppliers may vary further on increasing or decreasing the number of decision-makers, the number of suppliers to be evaluated, and the number of supplier selection criteria.

4.3.2 Sensitivity analysis

Sensitivity analysis is performed to check the extent to which the results coming from the methods can vary depending on the changes in the inputs of the methods, namely, supplier selection criteria; the number of suppliers; and the number of decision-makers. While there could be N number of scenarios for which sensitivity analysis can be done, only Fuzzy-TOPSIS method results are considered, which allows us to see the dynamics of results based on changing the number of suppliers, number of supplier selection criteria, and number of decision-makers. So, the inputs of Fuzzy-TOPSIS will be changed to check the variation in the results.

Scenario A: Three experts: DM1, DM2, and DM3 instead of four, are involved in the evaluation while all other inputs are constant. The decision matrix for criteria evaluation based three expert judgements is shown in Figure 4.8.

	DM1	DM2	DM3
Cost	(0, 0, 0.1)	(0.5, 0.7, 0.9)	(0.7, 0.9, 1.0)
Lead Time	(0.7, 0.9, 1.0)	(0.9, 1.0, 1.0)	(0, 0, 0.1)
Quality	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)	(0.7, 0.9, 1.0)
Flexibility	(0, 0.1, 0.3)	(0.7, 0.9, 1.0)	(0, 0, 0.1)
Operational efficiency	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0, 0, 0.1)
Innovation	(0, 0.1, 0.3)	(0.9, 1.0, 1.0)	(0.3, 0.5, 0.7)
Trust	(0.9, 1.0, 1.0)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Location	(0, 0.1, 0.3)	(0, 0, 0.1)	(0.3, 0.5, 0.7)
Sustainable Operations	(0.5, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.5, 0.7, 0.9)

Figure 4.8: Decision matrices for criteria evaluation using three experts' evaluation

Subsequently, the decision matrix for supplier evaluation based on three experts (DM1, DM2, and DM3) judgements is shown in Figure 4.9 for their evaluation based on ‘Cost’ criteria.

	DM1	DM2	DM3
Supplier A	(9, 10, 10)	(7, 9, 10)	(5, 7, 9)
Supplier B	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)
Supplier C	(0, 1, 3)	(0, 1, 3)	(1, 3, 5)
Supplier D	(7, 9, 10)	(9, 10, 10)	(1, 3, 5)
Supplier E	(0, 1, 3)	(9, 10, 10)	(7, 9, 10)
Supplier F	(0, 1, 3)	(9, 10, 10)	(1, 3, 5)
Supplier G	(1, 3, 5)	(9, 10, 10)	(5, 7, 9)
Supplier H	(1, 3, 5)	(9, 10, 10)	(7, 9, 10)
Supplier I	(0, 0, 1)	(9, 10, 10)	(5, 7, 9)
Supplier J	(5, 7, 9)	(1, 3, 5)	(7, 9, 10)

Figure 4.9: Example of a decision matrix for the supplier rating for ‘Cost’ criteria using three experts’ evaluation

After building all the decision matrices for supplier evaluation based on a total of nine criteria selected for this study, the final supplier ranking is obtained after the final computation and is shown below in Figure 4.10.

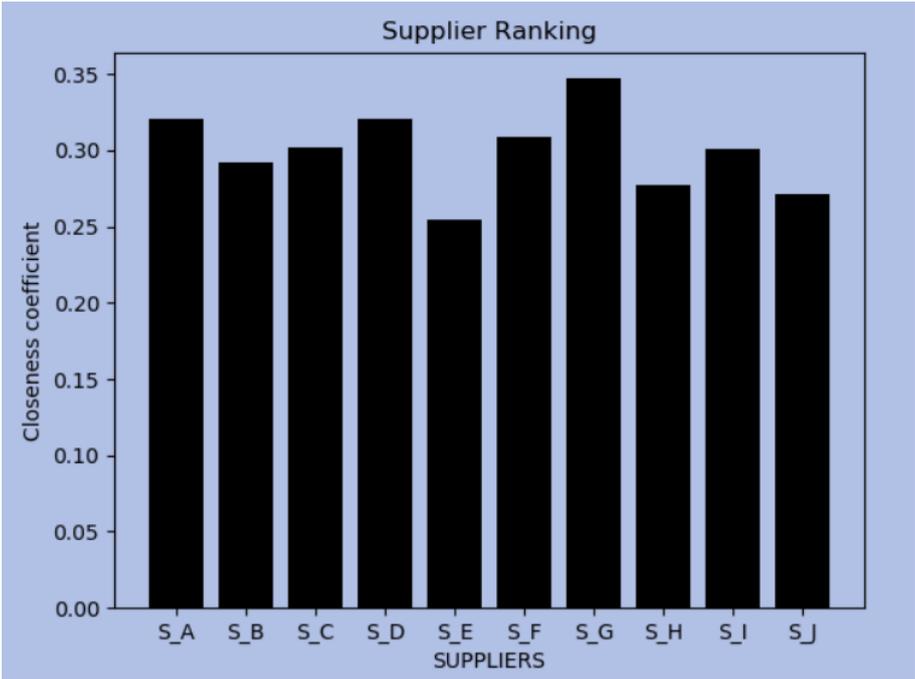


Figure 4.10: Supplier ranking by Fuzzy-TOPSIS method with three experts’ evaluation

Scenario B: While DM3 is excluded, three experts, DM1, DM2, and DM4, are involved in the evaluation while all other inputs are constant. The decision matrix for criteria evaluation based three expert judgements is shown in Figure 4.11.

	DM1	DM2	DM4
Cost	(0, 0, 0.1)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Lead Time	(0.7, 0.9, 1.0)	(0.9, 1.0, 1.0)	(0.1, 0.3, 0.5)
Quality	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)	(0.1, 0.3, 0.5)
Flexibility	(0, 0.1, 0.3)	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)
Operational efficiency	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0.9, 1.0, 1.0)
Innovation	(0, 0.1, 0.3)	(0.9, 1.0, 1.0)	(0, 0.1, 0.3)
Trust	(0.9, 1.0, 1.0)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Location	(0, 0.1, 0.3)	(0, 0, 0.1)	(0.1, 0.3, 0.5)
Sustainable Operations	(0.5, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)

Figure 4.11: Decision matrices for criteria evaluation using three experts' evaluation

Subsequently, the decision matrix for supplier evaluation based on three experts (DM1, DM2, and DM4) judgements is shown in Figure 4.12 for their evaluation based on 'Cost' criteria.

	DM1	DM2	DM4
Supplier A	(9, 10, 10)	(7, 9, 10)	(0, 1, 3)
Supplier B	(3, 5, 7)	(5, 7, 9)	(0, 0, 1)
Supplier C	(0, 1, 3)	(0, 1, 3)	(3, 5, 7)
Supplier D	(7, 9, 10)	(9, 10, 10)	(0, 1, 3)
Supplier E	(0, 1, 3)	(9, 10, 10)	(5, 7, 9)
Supplier F	(0, 1, 3)	(9, 10, 10)	(1, 3, 5)
Supplier G	(1, 3, 5)	(9, 10, 10)	(1, 3, 5)
Supplier H	(1, 3, 5)	(9, 10, 10)	(9, 10, 10)
Supplier I	(0, 0, 1)	(9, 10, 10)	(0, 1, 3)
Supplier J	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)

Figure 4.12: Example of a decision matrix for the supplier rating for 'Cost' criteria using three experts' evaluation

After building all the decision matrices for supplier evaluation based on the total of nine criteria selected for this study, the final supplier ranking is obtained after the final computation and is shown below in Figure 4.13.

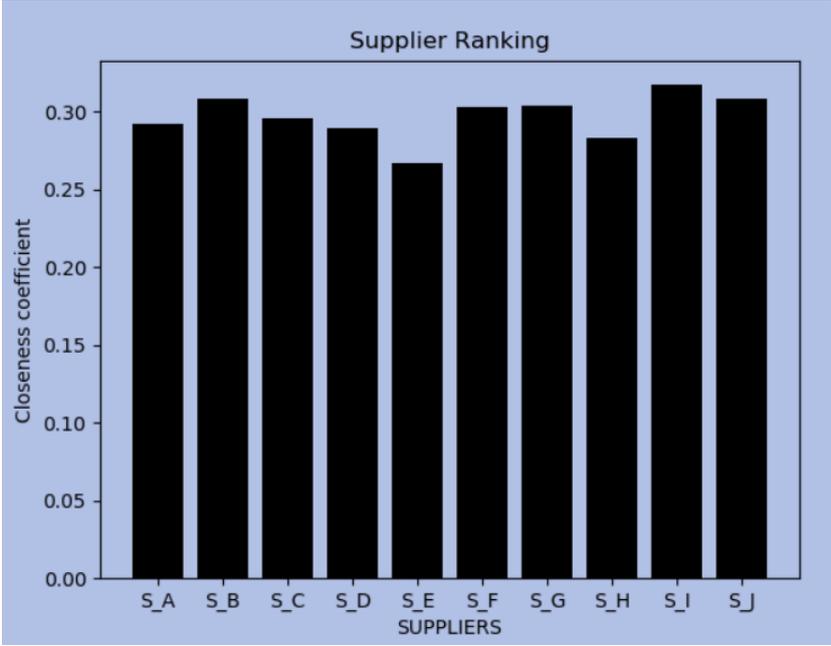


Figure 4.13: Supplier ranking by Fuzzy-TOPSIS method with three experts’ evaluation

Scenario C: While DM2 is excluded, three experts: DM1, DM3, and DM4, are involved in the evaluation while all other inputs are constant. The decision matrix for criteria evaluation based three expert judgements is shown in Figure 4.14.

	DM1	DM3	DM4
Cost	(0, 0, 0.1)	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)
Lead Time	(0.7, 0.9, 1.0)	(0, 0, 0.1)	(0.1, 0.3, 0.5)
Quality	(0, 0.1, 0.3)	(0.7, 0.9, 1.0)	(0.1, 0.3, 0.5)
Flexibility	(0, 0.1, 0.3)	(0, 0, 0.1)	(0.5, 0.7, 0.9)
Operational efficiency	(0, 0.1, 0.3)	(0, 0, 0.1)	(0.9, 1.0, 1.0)
Innovation	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0, 0.1, 0.3)
Trust	(0.9, 1.0, 1.0)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Location	(0, 0.1, 0.3)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)
Sustainable Operations	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)

Figure 4.14: Decision matrix for criteria evaluation using three experts' evaluation

Subsequently, the decision matrix for supplier evaluation based on three experts' (DM1, DM3, and DM4) judgements is shown in Figure 4.15 for their evaluation based on 'Cost' criteria.

	DM1	DM3	DM4
Supplier A	(9, 10, 10)	(5, 7, 9)	(0, 1, 3)
Supplier B	(3, 5, 7)	(5, 7, 9)	(0, 0, 1)
Supplier C	(0, 1, 3)	(1, 3, 5)	(3, 5, 7)
Supplier D	(7, 9, 10)	(1, 3, 5)	(0, 1, 3)
Supplier E	(0, 1, 3)	(7, 9, 10)	(5, 7, 9)
Supplier F	(0, 1, 3)	(1, 3, 5)	(1, 3, 5)
Supplier G	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
Supplier H	(1, 3, 5)	(7, 9, 10)	(9, 10, 10)
Supplier I	(0, 0, 1)	(5, 7, 9)	(0, 1, 3)
Supplier J	(5, 7, 9)	(7, 9, 10)	(1, 3, 5)

Figure 4.15: Example of a decision matrix for the supplier rating for 'Cost' criteria using three experts' evaluation

After building all the decision matrices for supplier evaluation based on the total of nine criteria selected for this study, the final supplier ranking is obtained after the final computation and is shown below in Figure 4.16.

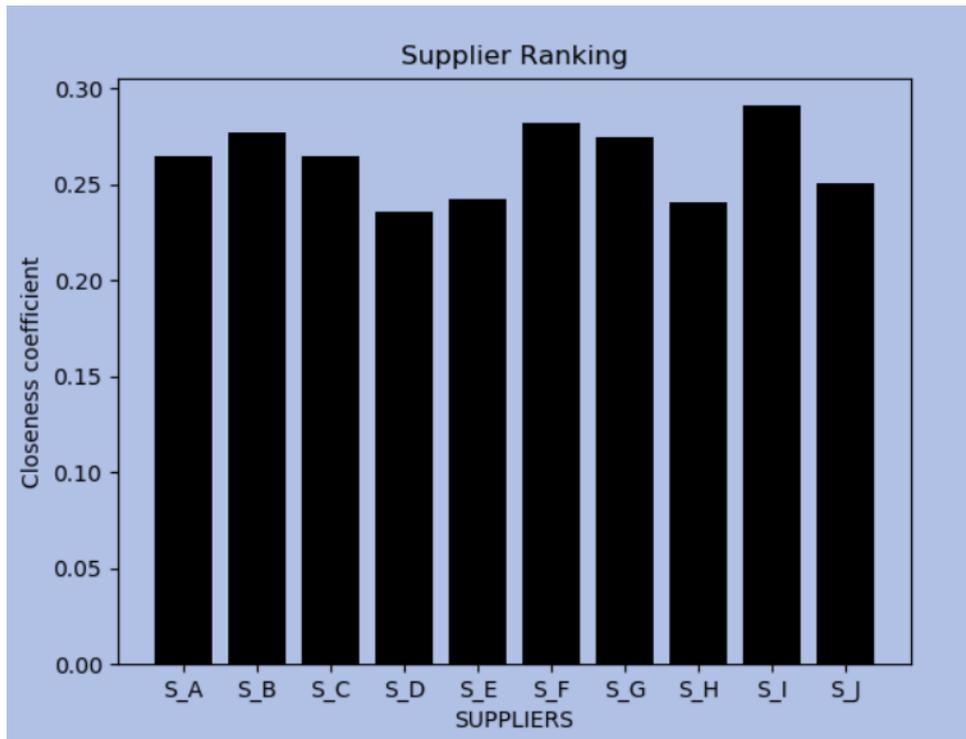


Figure 4.16: Supplier ranking by Fuzzy-TOPSIS method with three experts' evaluation

Scenario D: While DM1 is excluded, three experts: DM2, DM3, and DM4, are involved in the evaluation while all other inputs are constant. The decision matrix for criteria evaluation based three expert judgements is shown in Figure 4.17.

	DM2	DM3	DM4
Cost	(0.5, 0.7, 0.9)	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)
Lead Time	(0.9, 1.0, 1.0)	(0, 0, 0.1)	(0.1, 0.3, 0.5)
Quality	(0.1, 0.3, 0.5)	(0.7, 0.9, 1.0)	(0.1, 0.3, 0.5)
Flexibility	(0.7, 0.9, 1.0)	(0, 0, 0.1)	(0.5, 0.7, 0.9)
Operational efficiency	(0.3, 0.5, 0.7)	(0, 0, 0.1)	(0.9, 1.0, 1.0)
Innovation	(0.9, 1.0, 1.0)	(0.3, 0.5, 0.7)	(0, 0.1, 0.3)
Trust	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
Location	(0, 0, 0.1)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)
Sustainable Operations	(0.1, 0.3, 0.5)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)

Figure 4.17: Decision matrix for criteria evaluation using three experts' evaluation

Subsequently, the decision matrix for supplier evaluation based on three experts' (DM2, DM3, and DM4) judgements is shown in Figure 4.18 for their evaluation based on 'Cost' criteria.

	DM2	DM3	DM4
Supplier A	(7, 9, 10)	(5, 7, 9)	(0, 1, 3)
Supplier B	(5, 7, 9)	(5, 7, 9)	(0, 0, 1)
Supplier C	(0, 1, 3)	(1, 3, 5)	(3, 5, 7)
Supplier D	(9, 10, 10)	(1, 3, 5)	(0, 1, 3)
Supplier E	(9, 10, 10)	(7, 9, 10)	(5, 7, 9)
Supplier F	(9, 10, 10)	(1, 3, 5)	(1, 3, 5)
Supplier G	(9, 10, 10)	(5, 7, 9)	(1, 3, 5)
Supplier H	(9, 10, 10)	(7, 9, 10)	(9, 10, 10)
Supplier I	(9, 10, 10)	(5, 7, 9)	(0, 1, 3)
Supplier J	(1, 3, 5)	(7, 9, 10)	(1, 3, 5)

Figure 4.18: Example of a decision matrix for the supplier rating for 'Cost' criteria using three experts' evaluation

After building all the decision matrices for supplier evaluation based on the total of nine criteria selected for this study, the final supplier ranking is obtained after the final computation and is shown below in Figure 4.19.

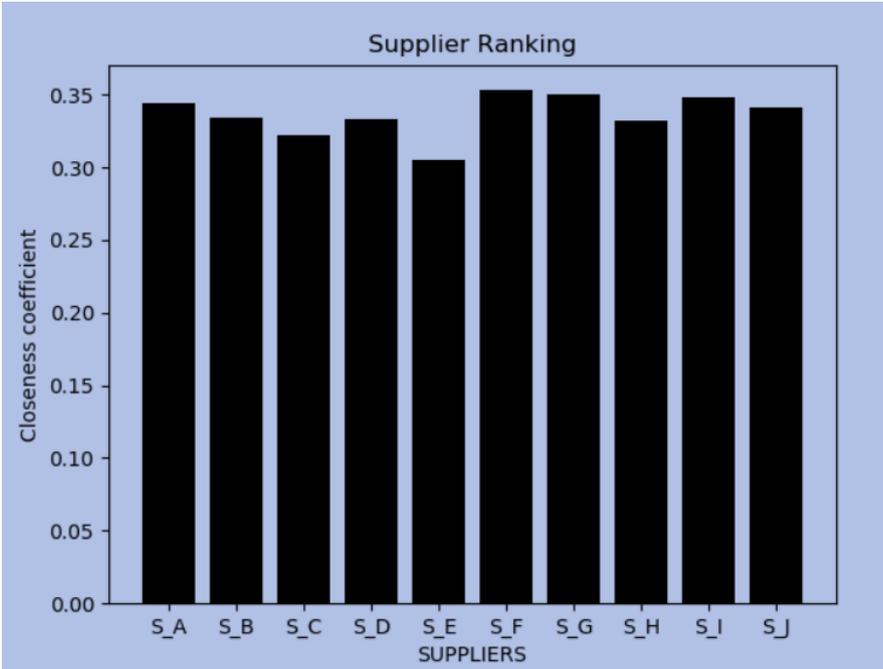


Figure 4.19: Supplier ranking by Fuzzy-TOPSIS method with three experts' evaluation

On comparison of the sensitivity analysis result (Figure 4.10), where the evaluation of only three experts was used while interchangeably removing one expert judgement, with the result from Fuzzy-TOPSIS method (Figure 4.7) wherein four experts were involved, it is clearly visible that the supplier ranking varies significantly, For example, the best three raw material suppliers in Fuzzy-TOPSIS method with four experts are *Supplier F*; *Supplier B*; and *Supplier C*; while in the Fuzzy-TOPSIS method with three experts as in scenario A, the best three suppliers in are *Supplier G*; *Supplier A*; and *Supplier D*, the comparison of the same is shown in Figure 4.20

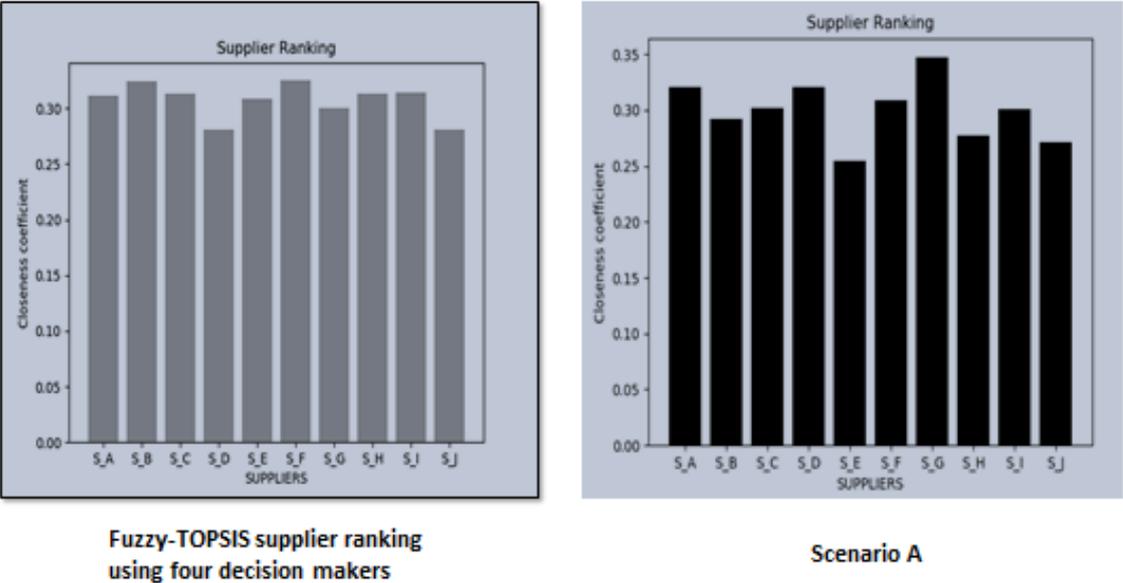


Figure 4.20: Comparison of supplier ranking by Fuzzy-TOPSIS method with the ranking from *Scenario A* created for sensitivity analysis

The sensitivity analysis results are illustrated for each scenario in Figure 4.21.

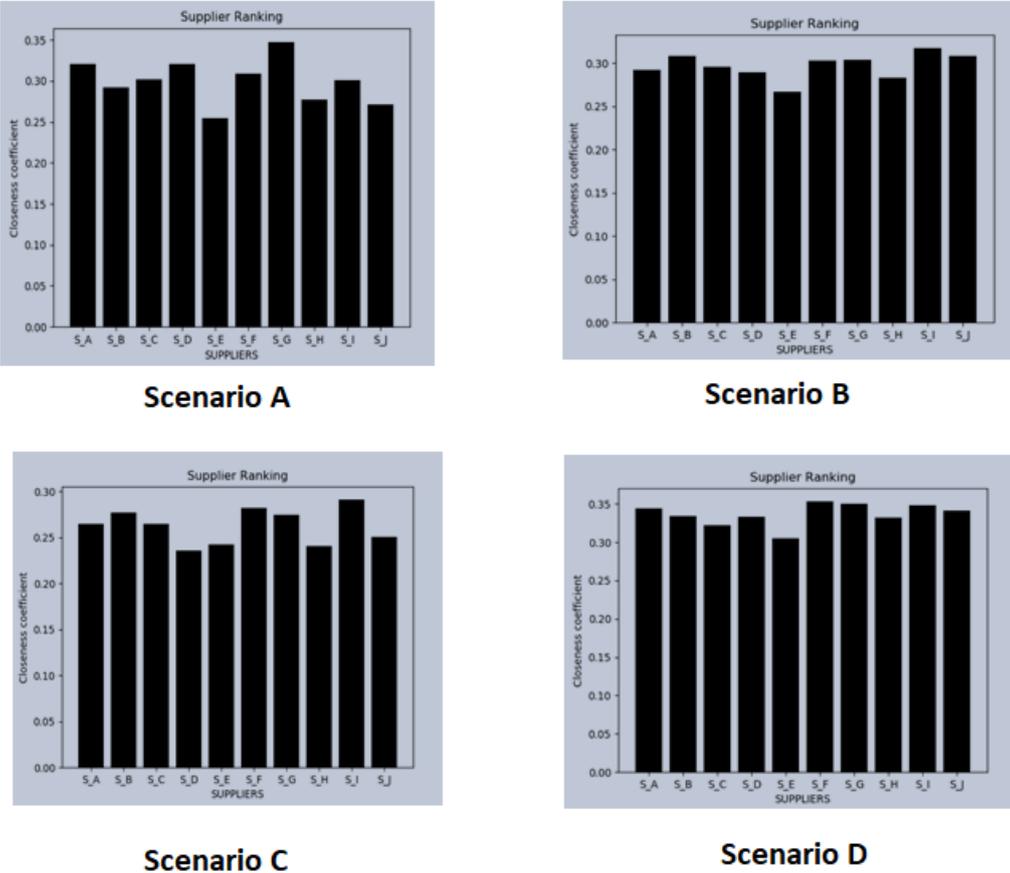


Figure 4.21: Comparison of supplier ranking by Fuzzy-TOPSIS method for four different scenarios created for sensitivity analysis

From the sensitivity analysis, it is evident that the supplier ranking result from Fuzzy-TOPSIS method significantly varies depending on the number of decision-makers, who participate in the evaluation process. In other words, judgement evaluations by different decision-makers could conflict with each other and significantly influence the supplier ranking.

4.4 Conclusion

This chapter aimed to address the first research question (RQ1), i.e. how the decision problem of raw material supplier selection for small-series fashion industry can be solved. Based on the obtained results from the applied MCDM methods, RQ1 is addressed, and the effective

approach for raw material supplier selection is developed for the static decision making in small-series fashion SCM.

Firstly, nine supplier selection criteria are selected as main important strategies of the small-series fashion retailers from the point of view of consumer choices and the changes in the fashion business models due to the adoption of e-commerce and digital technology. Further, these criteria are ranked based on AHP computation, and it is observed that the main important criteria are cost, lead time and quality. Next, criteria weights are inputted into the TOPSIS model, and evaluation of ten raw material small-series fashion suppliers corresponding to each one of nine supplier selection criteria by an industry expert is performed. As a next step, Fuzzy-TOPSIS was implemented by involving four industry expert's judgement on criteria importance as well as suppliers' evaluation on each criterion, and the results are achieved in terms of the final ranking of best suppliers.

Furthermore, sensitivity analysis of the performance of Fuzzy-TOPSIS method is performed to check the influence of change in the number of decision-makers participating in the criteria and supplier evaluation process, and it is observed from the results that change in the number of decision-makers, while keeping the number of criteria and the number of suppliers constant, significantly alters the final ranking of suppliers.

Overall, results achieved in this study are of great significance for the decision making in today's small-series fashion SCM and are promising to solve raw material supplier selection problem. It is important to highlight that the approach used in this study could be implemented for small-series fashion SCM for which the reliable and efficient raw material suppliers are critical. In the context of group decision making, the experimental study conducted in this chapter provides useful tools to investigate the importance of supplier selection criteria and suppliers. The judgements of experts on qualitative and quantitative

aspects of criteria are successfully aggregated. The approach adopted in this study is unique in terms of identifying key strategically important criteria for the digital small-series fashion supply chain management, and therefore, it constitutes a practical tool to solve raw material supplier selection problem.

Chapter 5

Dynamic supplier prediction for the small-series fashion product order fulfilment

The first stage of supplier selection problem in the small-series fashion industry, i.e. raw material supplier selection is addressed as the first research question (RQ1) that has been discussed previously in Chapter 1. In this chapter, the second research question (RQ2), i.e. how the best suitable suppliers for the fulfilment of newly arriving customer orders of small-series fashion products can be predicted in a real-time? In this chapter, RQ2 is addressed using machine learning methods that were applied to the real product sales data from a European small-series fashion company.

Small-series fashion industry is characterized by rapidly varying features of designs and product styles, and increasing customer preferences for personalized products. In recent years, there has been a shift in traditional fashion SC as fashion market is increasingly adopting e-commerce retailing. Given the growing data repositories in the companies' databases through e-shopping platforms, it is not possible to manage the load of such complex datasets and deriving valuable insights for decision making is complex and inefficient (L. C. Wang et al., 2015). Supplier selection is one of the critical decision-making problems that fashion retailers always deal with as their business efficiency and profitability depends on how they source their product materials. In other words, suppliers are quite critical to fashion retailers' supply chain management. Classical mathematical methods to select the best suppliers are not appropriate to deal with a lot of information and criteria considered for the selection of suppliers (Brandenburg et al., 2014). Data mining techniques have been used for solving apparel logistic management problems such as locating warehouse and manufacturing plants; inventory management; transportation management; sales management, and so on. However,

data mining methods have not been used so far to solve supplier prediction problems in a big data environment of fashion logistic management. Big data has significantly transformed today's business models. Small-series fashion industry is following a similar trend, and decision making in a real-time by studying dynamically generated data is critical to the growth and sustainability of their business.

5.1 Brief problem statement

For the small-series fashion retailers, it is indispensable to choose the best suppliers who support their business processes by providing high quality customized products to their customers at the right time. The operational and business efficiency of fashion retailers largely depends upon their suppliers (Jafari Songhori et al., 2011). As small-series fashion market is largely operating by adopting e-commerce platforms and digital technology, fashion retailers often realize the need for an automated mechanism for selecting best suppliers who will be able to fulfil their customer demands. Given the recent advancements in the database management technologies and customer's increasing online shopping preferences, fashion companies retrieve a variety of information from their databases which can include customer choices, market trend, product features and demand etc. However, to utilize this information for decision making is often complex and laden with many difficulties. Supplier selection in the fashion industry is a highly critical and complex process as it entails multiple qualitative and quantitative criteria and the participation of many managers working in the supply chain management of companies. Typically, data mining technologies have been used for demand forecasting, market analysis, social media analysis of brand's popularity, etc. (Kim et al., 2005). However, the application of data mining methods for the prediction of the best suitable supplier corresponding to customers' specific demands has not been studied in academic research before. Therefore, authors in this paper aim to explore the applicability of data

mining methods such as supervised machine learning algorithms to predict the best suitable supplier, who can fulfil the product orders. Data mining methods have been applied for predicting customer demands for the products, social media analytics, market research etc. There is limited literature on the application of data mining methods on the supplier prediction decision problem in the small-series fashion industry. Data mining methods are usually applied on historical data to find the pattern in it and derive insights out of it. Building on this premise, our goal is to propose a data mining based methodological framework for the supplier prediction in the fashion industry.

To predict the supplier for customers order in future, data mining models need to be trained on the historical customer order data that include information of products' customized features. Data mining models extract as much information as possible from the dataset and derive the pattern in it (Giudici & Passerone, 2002).

The motivation behind exploring this study emerges from the increasing complexity of decision making in the context of small-series fashion SCM.

5.2 Methodology

5.2.1 Research framework

In order to explore RQ2 and how data mining methods can predict supplier from the customer order data, historical sales data provided by the European fashion company is used. The overall research framework is illustrated in Figure 5.1.

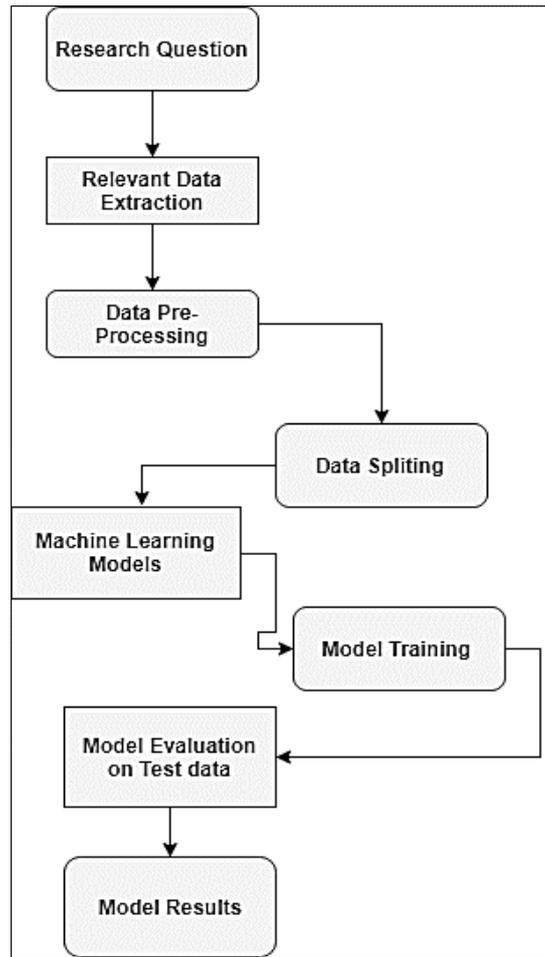


Figure 5.1: Research framework

5.2.2 Machine learning models and evaluation metrics

In this paper, the historical customer order data with labels were used; therefore, a supervised machine learning approach was adopted for this study. Supervised learning approach mainly includes regression and classification (Bishop & M., 2006).

Since the suppliers are unique labels in the dataset, classification models were used to predict the best supplier by including appropriate predictors in the dataset.

Classification models take inputs from various features in the dataset and give output in terms of a label or a class for the predicted variable (Perspective, 2015). Classification is of two

types depending on the number of classes to be predicted. If the classes to be predicted are two, it is known as binary classification, while in case of more than two classes, it becomes multi-class classification.

To derive the pattern out of qualitative features of data, rule-based classifiers such as kNN, RF, NN, naïve Bayes are generally used and give better performance (James et al., 2013). Therefore, these models have been used to predict the best matching suppliers. The detailed mathematical formulation of machine learning models used for this study is detailed in Chapter 3.

5.2.2.1 k-Nearest Neighbors (kNN)

kNN model is a non-parametric classification method which predicts the classes by computing the Euclidean distance between the data points in the features and the new data points. kNN classifies data points into labelled classes based on the similarity between them. kNN learns the patterns in the data iteratively and identifies the majority of similar 'k' nearest neighbours. The number of 'k' neighbours can be selected by users depending on the learning goal of the research problem.

5.2.2.2 Random Forest (RF)

RF model can be considered to be the extension of the Decision Trees algorithm. It builds decision trees by taking into account data points in the training dataset and gives output in terms of class label. The splitting nodes are decided based on the statistical probability of assigning a specific class to the data points, and furthermore, it averages them in order to predict the class.

5.2.2.3 Neural Networks (NN)

NN classifier mimics the human brain neurons that are characterized by multiple interconnected nodes of neurons, which carry information to the other nodes and ultimately produce output as a single node. This classifier is a popular technique for multi-class classification problem as it gauges interdependencies between the classes to be predicted.

5.2.2.4 Naïve Bayes (NB)

Naïve Bayes is a probabilistic classifier, which works based on the theory of Bayes' conditional probability theorem, and takes into account prior information available to compute the probability of a future event. It is used when the size of the dataset is small, and when features in the dataset are not correlated.

5.2.3 Evaluation Metrics

As outlined in Chapter 3, the performance and accuracy of the classification models are evaluated based on the metrics: Confusion matrix; Precision; Recall; F1; Area under the curve (AUC); and Classification Accuracy (CA) (Loh, 2011).

a. Confusion Matrix:

Confusion matrix presents an overall model performance in a tabular form, in which classes predicted correctly and incorrectly are summarized as follows.

True Positives (TP): correctly predicted class 1 as 1

True Negatives (TN): correctly predicted class 2 as 2

False Positives (FP): incorrectly predicted class 2 as 1

False Negatives (FN): incorrectly predicted class 1 as 2

The confusion matrix, as depicted in Figure 5.2, contains rows and columns; rows represent actual classes while columns represent predicted classes.

	<i>Class 1 Predicted</i>	<i>Class 2 Predicted</i>
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Figure 5.2: Confusion matrix

b. Precision:

Precision is the ratio of true positive classes to the number of actual positive classes and is formulated as follows:

$$Precision = TP / (TP + FP) \tag{5.1}$$

c. Recall:

Recall is the ratio of true positive observations to all the observations in the actual class.

$$Recall = TP / (TP + FN) \tag{5.2}$$

d. F1 score:

F1 score is the harmonic mean of recall and precision. The accuracy indicates the classifier's overall performance as it takes into account both false positives and false negatives, and is calculated as follows:

$$F1\ Score = 2 * (Recall * Precision) / (Recall + Precision) \tag{5.3}$$

e. Area under the Curve (AUC):

AUC gives us an aggregated performance measure for all possible classification thresholds. AUC is the probability of a model classifying positive observation higher than the negative one. AUC value ranges between 0 and 1.

f. Classification Accuracy (CA):

Classification Accuracy of the model is the fraction of correctly predicted observations. It is calculated as follows

$$\text{Classification Accuracy} = (TP+TN)/(TP + TN + FP + FN) \quad (5.4)$$

5.2.3 Data Source

To explore the RQ2, stated previously, the data from the database of European fashion brand were collected, which is specialized in various fashion products, including luggage and handbags. Due to the company data regulations, the European small-series fashion company provided us with historical one-month customer order data. The dataset was relatively small and originally contained 100 elements and 35 variables.

5.3.3.1 Data description

Given that the used data were labelled, supervised learning methods have been applied. The attributes in the original dataset and their description is given in Table 5.1. Ethical data guidelines have been followed to maintain the confidentiality and sensitivity of seven unique suppliers in the dataset. Next, supplier Id's were anonymized by assigning them labels such as A-G as shown in Table 5.1.

Table 5.1: Characteristics of the data

Data attributes	Description
Buy	Quantity of products bought
Panel	Seasonal availability of product
Proto/Dev	P= Product Prototype D= Customized product
Gender	U= Unisex; X= Male; D= Female
Business Line	Business Channels
Category	Product Category, e.g. Luggage, Bags, Accessories
Sub-Category	Sub-category of the products
Mtl	Product material, e.g. polyster, Nylon, Rubber, etc.
Supplier	Suppliers (Labelled as A, B, C, D, E, F, G)

5.3.3.2 Data preprocessing

The dataset is preprocessed by removing the noise in terms of missing values and outliers. Further, the dataset is split into trained, validation and test datasets by using deterministic random sampling as it ensures that the model is correctly fitted to the data without biasedness. To split data into train and test datasets, ‘80:20’ fraction is used. Then, k-fold cross-validation is applied on the trained data, and the default value for “k” is set to “10”. It is important to highlight that the features in the dataset are mostly categorical or nominal owing to which it is subject to encoding in order for machine learning models to be applied. Label encoding and subsequently, one-hot encoding is employed to transform the categorical features in the dataset into binary values.

Each classification model is then applied on trained, and prediction is done on the test data. Prediction accuracy and the model performances were evaluated according to the metrics corresponding to each model.

5.3 Experimental results

Classification models to predict supplier are applied on the trained data (80% of the original dataset); k fold crossed validation data (k = 10) and finally on the test data (20% of the original dataset). It is observed from Table 5.2, the model performance of kNN, RF, NN on the trained dataset gives 100% accuracy, while Naïve Bayes gives 86% accuracy. It means that the models are overfitting the data except for the NB model, and it implies that the models are highly biased.

Table 5.2: Model accuracy on trained data

Classifier	AUC	CA_Trained	F1	Precision	Recall
kNN	1	1	1	1	1
RF	1	1	1	1	1
NN	1	1	1	1	1
NB	0.99	0.867	0.88	0.922	0.867

The prediction accuracy of the models on trained data is shown in Figure 5.3 below.

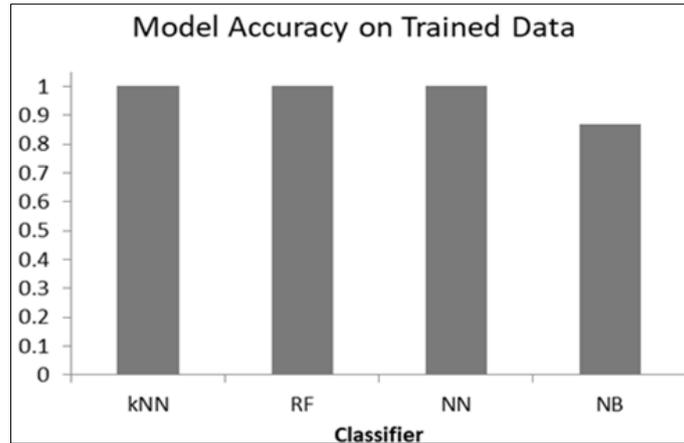


Figure 5.3: Model performance on trained data

To address the overfitting problem, k-fold cross-validation is applied to trained data with $k=10$. K-fold cross-validation subsets data into ten subsets, where nine subsets are used for model training and remaining one subset is used for model testing. The accuracy of the models on cross-validated data is averaged over all the subsets (folds), and the values are shown in Table 5.3.

Table 5.3: Model accuracy after cross-validation on trained data

Classifier	AUC	CA_CV	F1	Precision	Recall
kNN	0.935	0.783	0.755	0.73	0.783
RF	0.951	0.883	0.865	0.86	0.883
NN	0.937	0.8	0.782	0.772	0.8
NB	0.939	0.717	0.717	0.737	0.717

It can be observed that model accuracy is reduced after applying cross-validation on trained data, and it implies that models are not overfitting to the data. Prediction accuracy of ML models after cross-validation on trained data is depicted in Figure 5.4.

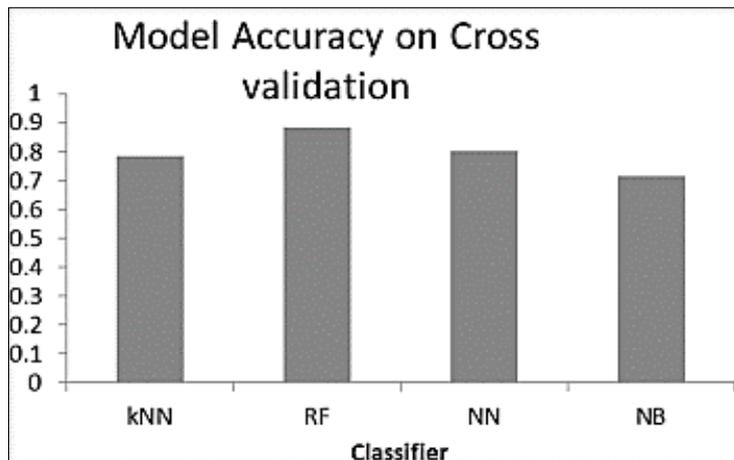


Figure 5.4: Model performance on cross-validation

Further, a supplier is predicted by applying models on the test data that were completely unfamiliar with the models during training as it was held out for the prediction. Classification accuracy of the models on test data is significantly lower than on the trained data. It is evident that the RF and kNN models outperform kNN and NB models while predicting suppliers on the test data. Classification accuracy of the models on test data is shown in Table 5.4.

Table 5.4: Model accuracy on test data

Classifier	AUC	CA_Test	F1	Precision	Recall
kNN	0.905	0.714	0.684	0.768	0.714
RF	0.933	0.786	0.81	0.857	0.786
NN	0.97	0.786	0.774	0.81	0.786
NB	0.97	0.714	0.702	0.821	0.714

The comparative performance of the ML classification models is depicted in Figure 5.5.

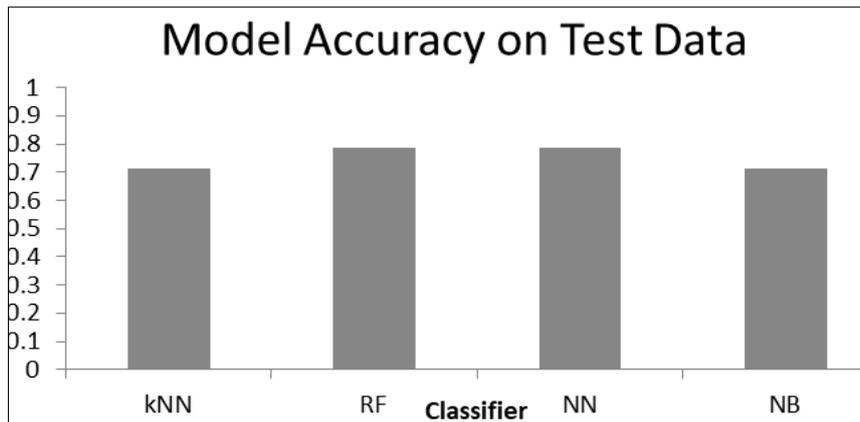


Figure 5.5: Model performance on test data

kNN, RF, NN, NB classification models are applied on the customer order data to predict small-series fashion product suppliers, and it is observed that the performance of RF and NN models is better than kNN and NB models. On comparison of the model accuracy with the accuracy on trained and cross-validation data, it is observed that the performance of RF and NN is consistent.

5.4 Discussion

It is evident from the results (Figure 5.5) that the ensemble RF and NN have performed better even though the data size was relatively small. Both the models have predicted all the supplier classes with high accuracy. For the given supplier prediction problem and the dataset used to train the classification algorithms, RF and NN outperform kNN and NB. However, it is difficult to argue as to which models are the best for general classification problems as they are different types of algorithms and function differently. K-NN is instance-based, and models are biased towards distance-based problems whereas NB is a probabilistic model and this assumes that each input features attributes are conditional independent (Ziegel, 2003)(Hastie et al., 2009)(Bishop, 2006). These both models are simple and easy to implement. However,

given the sheer simplicity, K-NN and NB models are often beaten by adequately trained and tuned models such as RF and NN.

The RF is an ensemble of trees for decision making. Each decision tree processes the sample in the ensemble and predicts the output class label (in case of classification). The decision trees in the RF models are independent of each other, and each tree can predict the final target value. In practice, classification tree ensembles perform very well due to their hierarchical structure. They are robust, scalable, and able to model non-linear decision boundaries. These models can be pruned using the number of trees, gain ratio, max depth.

Moreover, the NN is a network of neurons linked together and it learns from non-linear functions approximations. This model requires parameter tuning of hidden neurons layers, activation function, weight optimizer and the number of iterations (Kingma & Ba, 2015; Pedregosa FABIANPEDREGOSA et al., 2011). RF and NN can be tuned for enhancing the model performance and as a result, these both models have performed well for the garment supplier prediction problem. The default parameters are selected for the implementation of these models.

Moreover, the performance of the RF and NN is close to 79 %, which can further be improved by increasing the training data (for one year or more). It could be that the limitation of this study highlighting the lower than 90% classification accuracy can be overcome by improving the model parameters according to the size of the future dataset. Application of a further advanced classification model can also be explored when locating the problem of supplier prediction in a more advanced case-study based context.

5.5 Conclusion

In this study, the second research question (RQ2) is addressed, i.e. the supplier prediction problem for the new customer order, which entailed the sales information and ordered product features. ML methods are applied to the product sales data from the small-series fashion company to predict the best garment suppliers for the new customer orders. The advantages of applied ML methods are demonstrated with the experimental approach presented in this chapter in order to predict the assignment of a new customer order to the best supplier. The European fashion company that deals with the difficulty of analyzing customer order data and identifying the best matching supplier could greatly benefit from the results of this study as it could enable them to effectively predict the best matching supplier for the newly received order based on the classification of suppliers on the basis of customer order attributes.

In a small-series fashion business framework, selection of suppliers is a complex decision-making process and is based on the long term relationship with the suppliers. However, given the deep level of customization of products on the part of customers, it is difficult to make decisions with regard to suppliers as it is highly challenging and complex to study attributes in the customer order data and match them with the existing set of potential suppliers. In this study, data mining methods are utilized to solve the problem of supplier prediction in real-time for the new customer orders, and the results from this study indicate that the machine learning classification methods are promising to address this decision problem. The future extension of the study carried out in this chapter could be to enhance model performances by building large customer order dataset by periodically collecting the historical order data considered for the supplier prediction problem data. The major scope for the improvement in this study lies in the application of advanced ensemble techniques (Rathore & Kumar, 2017), (X. Yang et al., 2017) that are highly effective to improve the model performance by reducing

model biasedness and variance by building one predictive model out of several ML predictive models applied on the various subsets of data. Secondly, as the major requirement for the ML methods is the large historical dataset to solve decision problems in real-time, the study conducted in this chapter could be significantly improved by using more data from the industries and analyzing model performances on it. Moreover, in future, when the applied models will be deployed in production considering other business cases, customer order data could be enhanced by adding multiple product-related attributes as well as customers' online browsing behaviour that could effectively improve the model performances.

Chapter 6

Dynamic customer order assignment to the best garment suppliers

In this chapter, solving dynamic customer order assignment problem is the main research objective. The third research question (RQ3) of this thesis, as outlined in Chapter 2, is addressed. RQ3 aims to accomplish the second task in the supplier network co-ordination; the first task is the study carried out in Chapter 4, i.e. selection of raw material suppliers in a static manner.

The study carried out in this chapter proposes GA method based approach for dynamically allocating newly arriving customer orders of small-series fashion products to the best garment supplier among the pool of all the suppliers who compete among each other to fulfil those orders. Keeping business objectives in mind, small-series fashion companies need to make efficient decisions in regard to handling customer orders arriving in a real-time and assigning them to the best suppliers that help retailers achieve their goals. Since small-series fashion industry follows the *pull SC* system, meaning all the decisions related to sourcing finished customized fashion products are triggered after the customers send their orders via online platforms, which warrants a bottom-up approach in small-series fashion SCM. This study aims at addressing the aforementioned research problem, which is highly relevant for the decision context as outlined in RQ3.

In a typical fast-fashion framework, the orders generated by big fashion retailers are based on seasonal demand forecast, and they are characterized by a low degree of customization as the products are targeted towards mass consumption. Traditional fast-fashion supply chains operate in the so-called "*Push System*", which involves production planning and order

management triggered by the seasonal order forecast models that predict future customer demands based on customers' historical purchases.

Orders in the small-series fashion, on the other hand, are characterized by rapidly varying designs and product styles, and a high degree of product variability in terms of individual customer preferences and customization. Small-series fashion products have relatively long life cycle lengths, and a high degree of customization. In recent decades, traditional fashion retailing has been significantly transformed as the fashion market is increasingly adopting e-commerce retailing. Advances in the fashion e-commerce platforms allow customers to dynamically generate orders for the small-series customized products that need to be processed in a real-time. Given the growing customer order data repositories in the companies' databases through e-shopping platforms, it is challenging to manage the load of such complex order datasets, and processing these customer orders and allocating them to the best suitable suppliers in a real-time is a complex and difficult decision problem (Liang et al., 2020).

Small-series fashion operates in the "*Pull System*", wherein supplier selection for procurement, order management, production planning and distribution are driven by the real-time customer demands rather than by future demand forecasts. The key supply chain decisions are initiated after the customer orders are generated via e-commerce platforms in real-time. The mechanism of real-time customer order generation is triggered when customers' online purchase of customized fashion products initiates real-time data flows through the digital supply chain that constantly facilitates the dynamic movement of raw materials and accessories for the final product through the network of participant suppliers. The complexity arising from the analysis of customer order data and supplier attributes, and most importantly, the retailers' business objectives require the development of *Just-in-Time* (JIT) decision methods. The main relevance and significance of these methods are realized in

terms of reduced lead times, low return rates, smaller lot sizes, high levels of customer satisfaction, and sustainable supply chains.

There exists a broad approach viz., optimization-based decision methods in the existing literature for solving order planning problems. In work by (Ait-Alla et al., 2014), optimization-based mathematical models have been developed for solving production planning and scheduling problems, particularly in fashion industry considering that the orders are characterized by the varying costs associated with production and delivery time.

Although many studies primarily focused on minimizing production cost and production time, there are several studies such as (Betrand & van Ooijen, 2008),(Wong et al., 2014),(Wu et al., 2011) that considered solving multi-objective optimization problems involved in production capacity and order planning problems. In another interesting study by (Guo et al., 2015), a different approach of transforming multiple production planning objectives into one goal by using a weighted-sum method using goal programming. The broad methodologies that exist in the literature used for solving production planning include Genetic algorithm; Knowledge-based models, Hybrid models; Fuzzy logic models; and Expert system techniques.

Overall, the decision making in small-series fashion SCM is based on the customer demand-pull, unlike retailer-push supply chain models. Therefore, small-series fashion industry, following the JIT trend, needs efficient decision models for order processing and supplier allocation in a real-time by studying dynamically generated customer order data, and developing suitable models for the same is critical to their sustainability and business growth. To solve dynamic order allocation decision problem, Genetic Algorithm (GA), and a hybrid decision model comprised of the fusion of GA and TOPSIS methods are used. GA method is chosen for addressing the dynamic order assignment problem given its wide applications, popularity and the efficiency in solving multi-objective optimization problems (Coello Coello, 2006), (Lin & Chuang, 2007), (Rosso et al., n.d.), (Ombuki et al., n.d.).

6.1 Research problem statement

As discussed in the previous section, this study aims at solving RQ3, i.e. customer order assignment and garment supplier allocation problem based on Genetic Algorithm and TOPSIS based optimization methods.

For the small-series fashion retailers, it is indispensable to allocate customer orders to the best garment suppliers in a real-time, who support the business objectives of the retailers by providing high-quality end products to their customers in the right time. The operational and business efficiency of fashion retailers largely depends upon how efficiently they allocate customer orders to the most suitable garment suppliers. As fashion market adopting e-commerce platforms and technology, fashion retailers often realize the need for an automated and highly responsive mechanism for the real-time customer order allocation to the best matching garment suppliers from the perspective of the fulfilment of their business goals.

Given the recent advancements in the database management technologies and customer's online shopping preferences, fashion companies retrieve a variety of information from their databases which can include customer order attributes, crucial features of ordered product and demand quantity, etc. However, to utilize this information for the decision making related to identifying suitable garment suppliers that contribute to the order fulfilment is often a complex decision problem and is laden with many difficulties. Customer order allocation is performed based on the supplier data and customer order data analysis as a form of the input for the decision models.

There is a dearth of scientific methods in the existing literature that addresses this specific decision problem of order processing on the basis of customer order and supplier data analysis. Building on this gap, our goal is to develop a GA and TOPSIS method based model framework for the real-time order assignment in a batch-wise manner for the small-series

fashion products. To assign customers' orders to the best garment suppliers, GA and TOPSIS models are applied on the customer order data and supplier data that include information related to products and suppliers. GA and GA-TOPSIS methods are advantageous to address RQ3 given their ability to produce optimal solutions based on the objectives of the decision problem, customer and garment supplier data and the scope for including static criteria evaluation into the dynamic customer order assignment problem. The GA-TOPSIS method based developed mechanism is useful for the small-series fashion industry to prioritize several decision factors over others while allocating the customer orders to the garment suppliers.

The overarching research objective of this study, in line with the RQ3, is to dynamically allocate customer orders of the small-series fashion products to the most suitable fashion garment suppliers by using GA and TOPSIS methods considering retailers' business objectives.

6.2 Experimental work

In this section, an overall study experiment is described, in which a hybrid approach is adopted, which combines GA and GA-TOPSIS model within the context of customer order assignment problem in small-series fashion supply chain management.

The data input flow and the key steps involved in the application of the proposed GA and GA-TOPSIS model are illustrated in Figure 6.1. The first input that triggers the model application for the garment supplier selection problem solving is the customer order data that can be accessed from the fashion retailer's e-platform database. After the customers send their orders through e-commerce websites of the fashion brands, the finished garment or fashion product is to be manufactured and delivered to the customers directly or via the retailer's distribution centre. The second data input to the model is supplier data that entail suppliers capability related attributes.

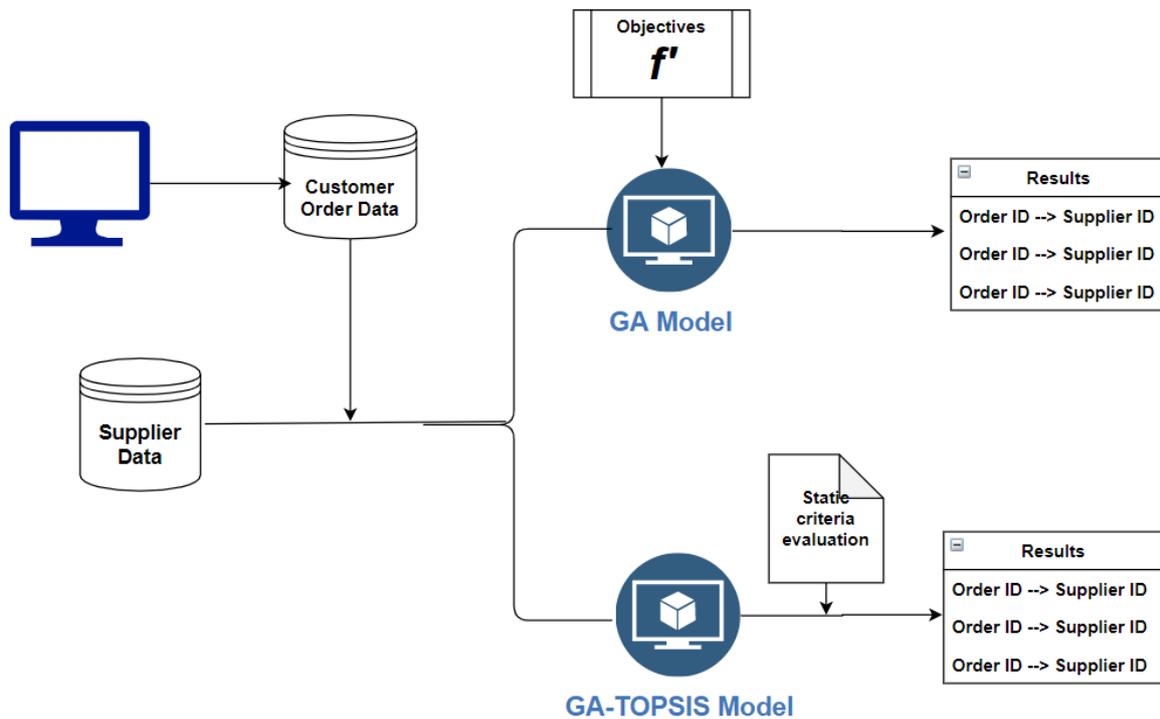


Figure 6.1: GA and GA-TOPSIS method based model framework

The fashion retailer's objectives related to the profit and customers' expected shipment time are central to the order assignment and the garment supplier selection process. These objectives are transformed into the mathematical functions that the applied GA model incorporates as objective functions. The GA model output is obtained in terms of optimal order assignments to the best garment suppliers that are assigned the highest score.

The second model illustrated in Figure 6.1 is GA-TOPSIS model that aims to enable retailers to use third input parameter, i.e. retailer's judgment on the relative importance of the static criteria for the order assignment model, which could be the crucial element in the order assignment decision. Since GA model does not facilitate the incorporation of the static criteria evaluation into the order assignment process, GA-TOPSIS hybrid model is applied in order to factor in qualitative aspects of the retailer's judgment of the suppliers.

Data input parameters:

The main inputs for the models used in the study are in terms of customer order data, as shown below in Figure 6.2, and garment supplier data are shown in Figure 6.3. Depending upon the retailers’ discretion and needs, retailers form a batch of orders received on each day or of the orders divided in specific day hours window, for example, the first batch of orders can be formed for the customer orders received between 9.00 AM and 14.00 PM, and the second batch of orders can be formed from the orders received between 14.00 PM and 20.00 PM. Alternatively, since the order frequency and batch size are small for small-series fashion products, retailers can also batch all the orders received in a given week.

Similarly, the number of candidate suppliers can vary as per the current status of retailers’ partnership with the number of suppliers existing in the supply chain. In this study, five competing candidate garment suppliers are considered for the evaluation to generate the sequence and assignment of the batch of 35 orders.

Order_ID	Quantity	Order Price	Expected Del_Time
111	2	80	12
112	5	180	15
113	3	115	12
.....
.....
.....
.....
.....
<i>Nth</i>	<i>Nth</i>	<i>Nth</i>	<i>Nth</i>

Figure 6.2: An example of a customer order datasheet

Customer order data attributes are described as following,

Order ID – ID assigned to the customer order

Quantity – Quantity of the product items ordered by the customer

Order Price - Total price of the order placed by the customer

Expected Del_Time – Customer’s expected delivery time for the product order

The supplier data that is used as an input for the order assignment decision problem is shown in Figure 6.3.

Supplier_ID	Product_Cost	Shipment_Cost	DEO	Production_Time	Shipment_Time
11	25	10	0	2	4
12	28	8	0	3	5
13	20	20	0	3	9
14	30	5	0	2	2
15	29	5	0	1	3

Figure 6.3: Supplier datasheet

Where,

Supplier ID – ID assigned to each candidate Supplier

Prod_Cost – Cost to the supplier to produce a unit quantity of the product

Shipment_Cost - Cost to the supplier to deliver ordered product to the customer

DEO = Delay to produce ordered product due to existing orders (in days)

Prod_Time – Time required by the supplier to produce a unit quantity of the ordered product

Shipment_Time - Time required by the supplier to deliver the ordered product to the customer

6.2.1 GA model for dynamic order assignment based

As explained in Section 6.2, the GA model optimizes fitness functions that are formulated based on the small-series fashion retailers’ objectives while selecting the garment suppliers

for the customer order fulfilment. In this section, objective functions and model parameters are illustrated.

Decision Variables:

Three decision variables, viz. Delivery date; Production cost; and Penalty are formulated in line with the objectives defined as fitness functions.

$$Del_Date_{ij} = DEO_j + Quantity_i * Production_Time_j + Shipment_Time_j \quad (6.1)$$

$$Production\ Cost_{ij} = Quantity_i * Product_Cost_j + Shipment_Cost_j + Penalty_{ij} \quad (6.2)$$

$$Penalty_{ij} = DEO_j * Penalty_rate \quad (6.3)$$

Fitness function:

Fitness function is formulated to evaluate the fitness of each chromosome into the solution set, and GA compute the fitness value/score of each individual from the population by bringing the chromosome into it, the higher fitness value corresponds to the better performance of the chromosome. With GA, two optimization problems are solved viz. profit maximization and lead time minimization for each order assignment. The input parameters are fixed as per the customer order and supplier data. GA computes the fitness function score for each supplier corresponding to each customer order using the input parameter values from the data. GA is an iterative process where solutions (fitness score of each supplier) improve over each successive generation. The process of fitness score improvement continues over the set number of generations until the satisfactory solution is obtained as per the set target score.

To match the retailers’ objectives, the fitness functions are formulated, as shown in Eq. 6.4 and Eq. 6.5:

Objective 1: To minimize the lead time delay for each order

$$Late_{ij} = Del_Date_{ij} - Del_Time_i \quad (6.4)$$

Objective 2: To maximize the profit for each order

$$Profit_{ij} = Price_i - Production_Cost_{ij} \quad (6.5)$$

Encoding:

In the implementation of GA, each set of solutions embedded into a chromosome, and after the process of chromosome crossover and mutation, a new set of solutions are produced. This process is repeated, and the best solution produced over the selected generations as the optimal solution is chosen for the optimization problem.

A batch of total 35 customer orders for which the best suppliers are to be selected out of 5 candidate suppliers who will have firstly, the minimum delay time for each order fulfilment, and secondly, the maximum profit for the retailer on each order.

No. of orders (I) = 35

Therefore, no. of genes in the chromosomes = I (35)

The chromosome compilation:

Order IDs	1	2	3	$I-1$	I
Chromosomes	Supplier ID	Supplier ID	Supplier ID	Supplier ID	$J-1$	J

Chromosome Selection:

Fitness function formulated above computes the fitness values for each chromosome according to which the probability of chromosome selection is determined as per the widely used Roulette wheel method for probability computation. Individuals representing each

chromosome are evaluated using the fitness score, and those with a high score are more likely to be selected for next iteration for the genetic transmission, and those with the low fitness score will be less likely to pass over their genetic material.

$$FP = \frac{F_i}{\sum_i^n F_i} \quad (6.6)$$

Experimental genetic parameters:

Population size = 100

Crossover rate = 0.8

Mutation rate = 0.2

Generations = 200

Termination criterion: The GA algorithm runs until it fulfils the predefined termination criterion. GA stops when the criterion of a maximum number of iterations is achieved. Moreover, several other termination criteria can be applied, such as the ration of mean fitness score to the maximum fitness score for a generation. Once the final generation is reached, input parameters associated with the best chromosome is considered to be the optimal solution for the chosen optimization problem.

6.2.2 GA-TOPSIS model for order assignment based on both static and dynamic criteria

In line with the static raw material supplier selection decision problem addressed in Chapter 4, GA-TOPSIS hybrid model is applied in order to integrate criteria evaluation, both static and dynamic supplier selection criteria, into the garment supplier selection decision making. The rationale behind integrating the evaluation of suppliers of based on supplier selection criteria with the dynamic garment supplier selection model, i.e. GA model, is that it allows fashion retailers to incorporate the subjective evaluation of their garment suppliers using TOPSIS evaluation scale. The applied GA-TOPSIS hybrid model aims to facilitate the novel, unique

and effective mechanism for decision making based on retailers' historical judgements of their suppliers' historical performance, and not merely based on the dynamically varying supplier and customer data. The illustration of GA-TOPSIS model is depicted in Figure 6.4. Figure 6.4 describes the overall flow of steps involved in the static raw material supplier selection and dynamic customer order assignment to the best garment suppliers for the order fulfilment.

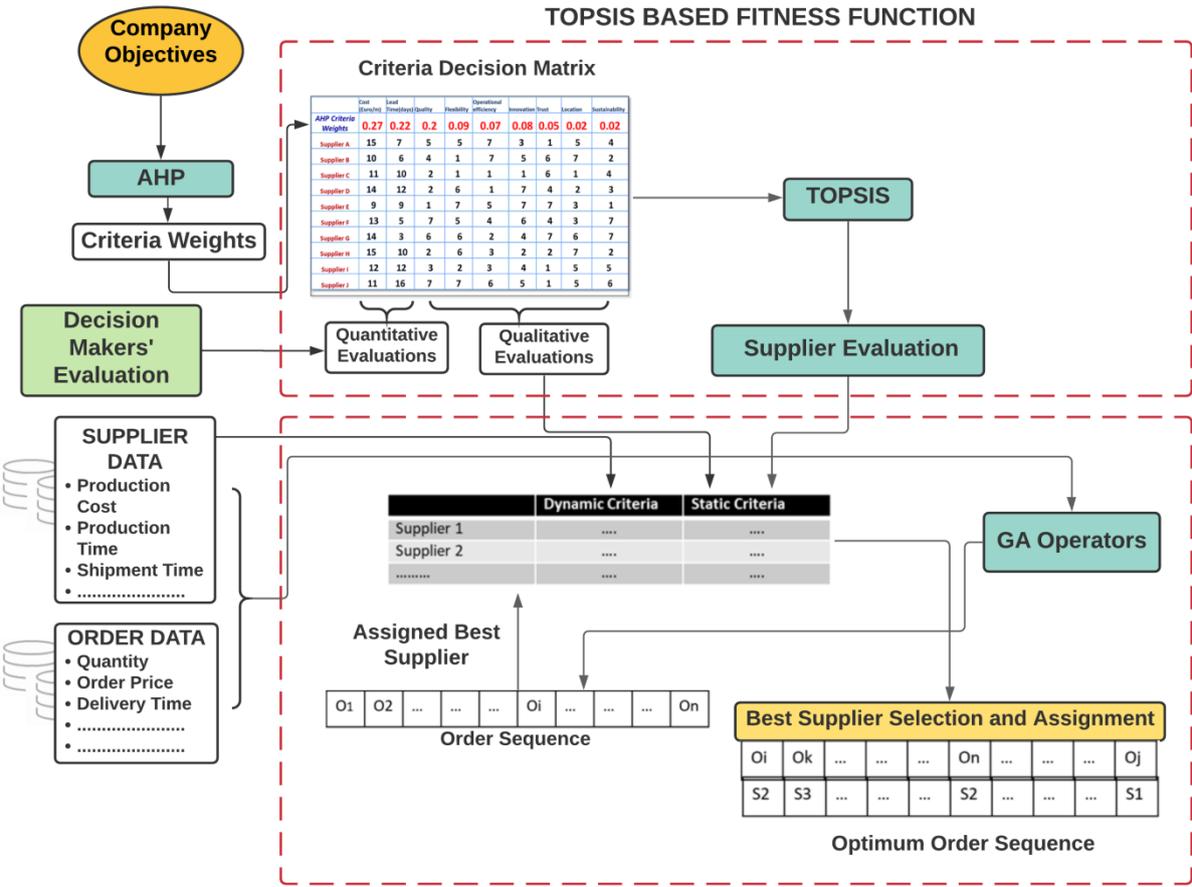


Figure 6.4: Dynamic order batch optimization using GA-TOPSIS model

In this context, firstly, the garment supplier selection problem solving is initiated by building decision matrix in which decision maker evaluates the importance of each criterion in a pairwise manner using the TOPSIS evaluation scale. The first decision matrix, as the first input parameter for the GA-TOPSIS model, for evaluating supplier selection criteria is built

using the Saaty's comparison scale presented in Chapter 4 (see Table 4.3) and is shown in Figure 6.5.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	X	Y
<i>Delay</i>	1/X	1	Z
<i>Quality</i>	1/Y	1/Z	1

Figure 6.5: Decision matrix for evaluating supplier selection criteria

The values used in the decision matrix (Figure 6.5) are described as follows

X – Expert's evaluation value for the comparison between *Cost* and *Delay*

Y- Expert's evaluation value for the comparison between *Cost* and *Quality*

Z – Expert's evaluation value for the comparison between *Delay* and *Quality*

The second input parameter in the form of a decision matrix that entails supplier evaluation values with respect to the static qualitative criteria and computed values of the dynamic criteria shown below in Figure 6.6. In this decision matrix, static criteria, i.e. *Quality*, has been used to evaluate all the participating suppliers using a Likert scale (see Table 4.6) as is presented in Chapter 4. For the criteria such as *Cost* and *Delay*, the GA model dynamically computes the evaluation values for the decision variables denoted in Eq. 6.1 and Eq. 6.2, respectively, for each supplier in the evaluation list based on the customer order and supplier data inputs (see Figure 6.2 and 6.3).

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Supplier 1</i>	Evaluated dynamically by Eq. 6.2	Evaluated dynamically by Eq. 6.4	4
<i>Supplier 2</i>			4
<i>Supplier 3</i>			3
<i>Supplier 4</i>			5
<i>Supplier 5</i>			5

Figure 6.6: Decision matrix for supplier evaluation

6.3 Results

6.3.1 GA output for order assignment with optimum lead time delay

Over 200 generations, GA yields an output in terms of a sequence of orders associated with the best supplier selected for each customer order whose fitness score is the highest among the other participating suppliers.

Optimum order sequence and supplier assignment results based on the GA output according to the first objective, i.e. *To minimize the lead time delay for each order*, is shown below in Figure 6.7. The GA result is based on the two data inputs viz. customer order data (Figure 6.2) and supplier data (Figure 6.3) as described in Section 6.2.

Order_ID	Assigned Supplier_ID
117	15
214	12
111	12
124	14
118	15
122	15
113	15
116	11
114	14
120	11
127	11
126	11
218	14
119	15
311	15
130	13
123	15
125	14
219	13
313	12
115	13
129	15
112	13
215	14
217	15
121	11
128	14
213	12
212	11
314	12
220	13
216	14
312	14
211	15
315	15

Figure 6.7: GA output for optimum lead time delay

6.3.2 GA output for order assignment with optimum profit

With the same customer order and supplier data inputs, as used for the GA result in Section 6.2.1, the second objective of the retailer, i.e. *To maximize the profit of the retailer for each*

order, is solved by running GA model that yielded optimum order sequence and supplier assignment results, as shown in Figure 6.8.

Order_ID	Assigned Supplier_ID
220	11
114	13
112	13
113	13
124	13
111	13
313	11
121	11
127	13
315	13
213	13
115	13
117	15
314	13
211	13
312	13
119	13
215	13
212	13
129	11
128	13
218	13
311	13
122	13
214	13
130	13
125	11
123	11
126	13
120	13
116	11
216	13
118	13
217	13
219	13

Figure 6.8: GA output for optimum profit

6.3.3 GA-TOPSIS output for order assignment with static and dynamic criteria evaluation input

In GA-TOPSIS model implementation, it is worthwhile to mention that the fitness score of each supplier is based on the decision-makers’ evaluation of supplier selection criteria that are presented as the first decision matrix (see Figure 6.5), and the supplier evaluation with respect to the static criteria, i.e. *Quality*, and dynamically computed criteria such as *Cost* and *Delay*, as presented in the second decision matrix (see Figure 6.6).

The configuration of the decision matrix as per the decision maker’s evaluation values assigned for the pairwise comparison of criteria is shown in Figure 6.9. This decision matrix is the first input for the GA-TOPSIS model, and the second input is the decision matrix shown in Figure 6.6.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	1	9
<i>Delay</i>	1	1	9
<i>Quality</i>	1/9	1/9	1

Figure 6.9: Decision matrix for the pairwise comparison of criteria

Based on the customer order data (Figure 6.2) and supplier data (Figure 6.3) inputs and two aforementioned decision matrices (see Figure 6.9 & Figure 6.6) inputs, the result of GA-TOPSIS model in terms of order sequence and supplier assignment is shown below in Figure 6.10.

Order_ID	Assigned Supplier_ID
116	13
220	13
315	13
312	13
123	15
216	13
211	13
118	15
314	13
217	15
311	15
125	15
111	15
119	15
130	15
313	15
114	15
218	15
213	15
113	15
129	15
120	15
117	15
214	15
115	15
112	15
126	15
122	15
212	15
219	15
128	15
124	15
121	15
215	15
127	15

Figure 6.10: GA-TOPSIS model output of the order assignment

As can be observed from the above result that Supplier 13 and Supplier 15 are the only suppliers who have been assigned all the customer orders by the model, the expert input in terms of TOPSIS evaluation of the suppliers based on the static criteria *Quality* regards Supplier 13 and Supplier 15 as the best supplier for the *Quality* as can be observed from Figure 6.6. The major factor influencing the assignment of orders to Supplier 15 could be its lowest production time (1 day) despite being the one with high production cost. High delay

and high production time for both the suppliers have been overshadowed by the *Quality* criteria as the experts considered it to be an extremely important criterion compared to *Cost* and *Delay* (see Figure 6.9).

Since GA_TOPSIS model allows the mechanism for including subjective judgements of the retailers in terms of pairwise comparison of supplier selection criteria using Saaty's scale (both static and dynamic) into the dynamic order assignment problem solving, it is of great significance to study the impact on the performance of GA-TOPSIS model in terms of the trade-off between best fitness scores of the three GA-TOPSIS output parameters, i.e. *Profit*, *Lead Time* and *Quality*.

To achieve this goal, TOPSIS evaluation of the suppliers based on three criteria presented in Figure 6.6 is used as a constant input for the GA-TOPSIS model. Customer order data and supplier data are the same as used for the previous results. The only input that is allowed to vary is the decision matrix presented in Figure 6.5, in which various configurations of retailers' evaluation of the supplier selection criteria are generated and used for GA-TOPSIS implementation. Therefore, four different scenarios viz. *Cost Oriented*; *Delay Oriented*; *Quality Oriented*; *Cost & Delay Oriented* are created by generating multiple configurations of supplier selection criteria evaluation decision matrix (see Figure 6.5). Each of these four configurations could be selected by the decision-makers based on the top priority criteria they select for fulfilling their business objectives while dynamically assigning the batch of customer orders to the best garment suppliers using GA-TOPSIS decision model.

The three variables viz. *X*; *Y*; and *Z* in the decision matrix shown in Figure 6.5 are allowed to take up evaluation values of relative importance from the Saaty's scale presented in Table 4.3. For each specific configuration generated in this context, GA-TOPSIS model is run, and the respective results are presented accordingly.

The nomenclature of the multiple versions of the GA-TOPSIS models that are run as per the input configurations based on the values of X ; Y ; and Z variables is defined as follows,

If $X = w$; $Y=w$; and $Z=w$, then GA-TOPSIS model is defined as GA_TOPSIS_{www} .

Where,

$$w = \{1, 2, 3, 5, 7, 9\}$$

The examples of the configuration values and the respective names of the GA-TOPSIS model versions for the following four scenarios are defined as follows,

Cost oriented:

In the *Cost* oriented scenario, the importance of *Cost* over the other two criteria, i.e. *Delay* and *Quality* is greater as per the evaluation variable values in Saaty’s scale.

Therefore, if $X = w$; $Y=w$; and $Z=1$, then GA-TOPSIS model is defined as GA_TOPSIS_{ww1} .

The example of a decision matrix for the *Cost* oriented scenario is shown in Figure 6.11.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	w	w
<i>Delay</i>	1/w	1	1
<i>Quality</i>	1/w	1	1

Figure 6.11: An example of a decision matrix for the *Cost* oriented scenario

Delay oriented:

In the *Delay* oriented scenario, the importance of *Delay* over the other two criteria, i.e. *Cost* and *Quality* is greater as per the evaluation variable values in Saaty’s scale.

Therefore, if $X = 1/w$; $Y=1$; and $Z=w$, then GA-TOPSIS model is defined as $GA_TOPSIS1/w-1-w$.

The example of a decision matrix for the *Delay* oriented scenario is shown in Figure 6.12.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	1/w	1
<i>Delay</i>	w	1	w
<i>Quality</i>	1	1/w	1

Figure 6.12: An example of a decision matrix for the *Delay* oriented scenario

Quality-oriented:

In the *Quality*-oriented scenario, the importance of *Quality* over the other two criteria, i.e. *Cost* and *Delay* is greater as per the evaluation variable values in Saaty’s scale.

If $X = 1$; $Y=1/w$; and $Z=1/w$, then GA-TOPSIS model is defined as $GA_TOPSIS1-1/w-1/w$.

The example of a decision matrix for the *Quality*-oriented scenario is shown in Figure 6.13.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	1	1/w
<i>Delay</i>	1	1	1/w
<i>Quality</i>	w	w	1

Figure 6.13: An example of a decision matrix for the *Quality*-oriented scenario

Cost & Delay oriented:

In the *Cost & Delay* oriented scenario, the importance of *Cost* and *Delay* over *Quality* is greater as per the evaluation variable values in Saaty’s scale.

If $X = 1$; $Y=w$; and $Z=w$, then GA-TOPSIS model is defined as $GA_TOPSIS1_{ww}$.

The example of a decision matrix for the *Cost & Delay* oriented scenario is shown in Figure 6.14.

	<i>Cost</i>	<i>Delay</i>	<i>Quality</i>
<i>Cost</i>	1	1	w
<i>Delay</i>	1	1	w
<i>Quality</i>	1/w	1/w	1

Figure 6.14: An example of a decision matrix for the *Cost & Delay* oriented scenario

Likewise, all the configurations within each of the four scenarios are generated, and the corresponding GA_TOPSIS models are defined as per the examples mentioned above. Next, the results in terms of best fitness scores for the three output parameters: Profit; Delay; and Quality are presented for four scenarios.

The computation of the best fitness score of the parameter *Quality* is illustrated as follows;

For a supplier S_i assigned to the customer order O_j by GA-TOPSIS model, let a_i be the evaluation value used in the decision matrix (Figure 6.6) with respect to each supplier. Let N be the total number of customer orders in the batch. The mean of evaluation value corresponding to each assigned supplier S_i to the customer order O_j is computed as follows;

$$Mean = \frac{\sum_{i=1}^N a_i}{N}$$

Min-max normalization method is used for normalizing the *Quality* score of each supplier in the resulting chromosome. From the decision matrix shown in Figure 6.6, Minimum (*Min*) and Maximum (*Max*) evaluation value, i.e. 3 and 5, respectively, for the normalization, is used.

Therefore, normalized best fitness *Quality* score for the GA-TOPSIS result is computed and scaled up to the best fitness *Profit* and *Lead time* parameter values as follows;

$$Best\ Quality\ fitness\ score = \frac{Mean - Min}{Max - Min} * 1000 = \frac{Mean - 3}{2} * 1000$$

Cost oriented scenario

GA-TOPSIS model is run for each configuration of supplier selection criteria evaluation, as shown in Figure 6.15, and the result in terms of comparison of best fitness scores of the

Profit, Lead Time and Quality parameters of the resulted order sequence corresponding to each configuration is shown in Figure 6.16.

Cost Oriented						
	GA_TOPSIS111	GA_TOPSIS221	GA_TOPSIS331	GA_TOPSIS551	GA_TOPSIS771	GA_TOPSIS991
Profit	918	921	1026	1035	1209	1320
Lead time	1404	1686	1535	1510	1733	2156
Quality	1000	971.4285714	828.57	742.86	628.57	557.14

Figure 6.15: GA-TOPSIS model outputs for Cost-oriented scenario

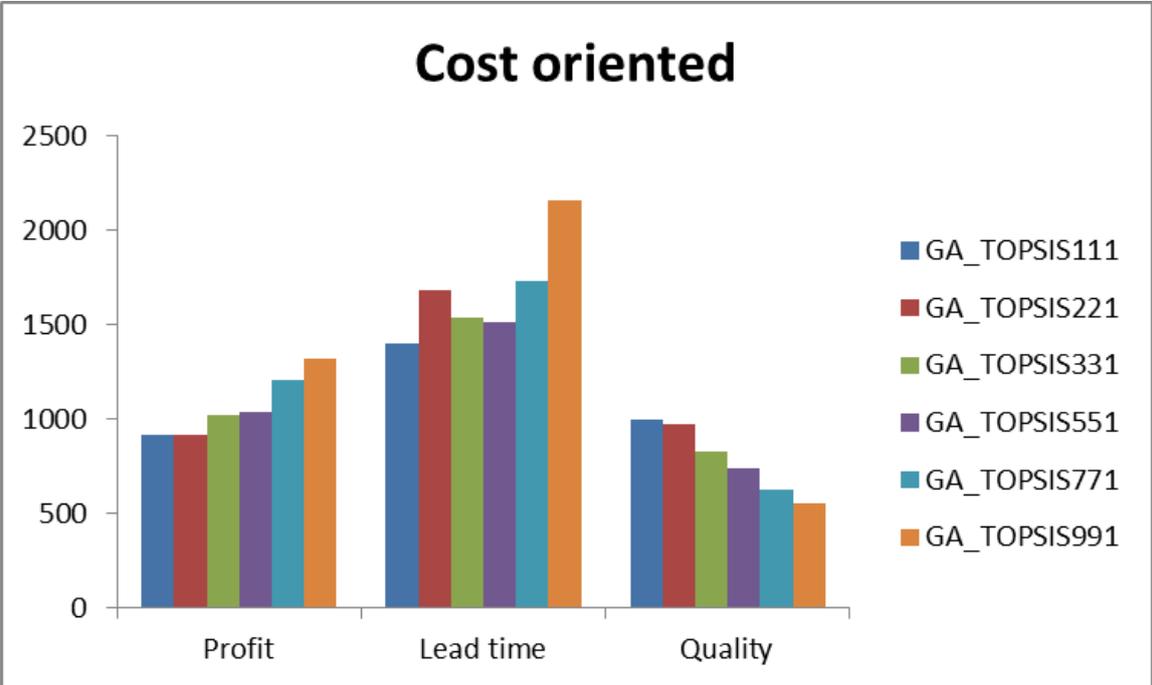


Figure 6.16: Comparison of the best fitness values of the GA-TOPSIS model output parameters for Cost-oriented scenario

From the Figure 6.16, it can be observed that as the configuration of supplier selection criteria evaluation progresses towards high importance of *Cost* over *Delay* and *Quality* on the Saaty’s scale, the profit with respect to the computed sequence of customer orders from the batch improves while the Quality score is decreasing. Although the *Lead time* is increasing and the

Quality score is decreasing gradually, in contrast to the goal of order sequencing result, there appears to be linear growth in the *Profit*. Overall, for Cost-oriented scenario, it can be concluded that the configuration of the supplier selection criteria evaluation embedding *Cost* as the most important criteria compared to *Delay* and *Quality* from the decision maker’s perspective has a significant influence on the *Profit*, *Lead time* and *Quality* score.

Delay oriented scenario

Delay oriented configurations of supplier selection criteria evaluation, as shown in Figure 6.17, are generated for each of which GA-TOPSIS model is run, and the comparison of the best fitness scores of *Profit*, *Lead Time* and *Quality* parameters of the resulted order sequence corresponding to each configuration computed by GA-TOPSIS model is shown in Figure 6.18.

Delay oriented						
	GA_TOPSIS111	GA_TOPSIS1/2-1-2	GA_TOPSIS1/3-1-3	GA_TOPSIS1/5-1-5	GA_TOPSIS1/7-1-7	GA_TOPSIS1/9-1-9
Profit	918	918	918	918	918	918
Lead time	1404	1442	1483	1345	1509	1354
Quality	1000	1000	1000.00	1000.00	1000.00	1000.00

Figure 6.17: GA-TOPSIS model outputs for Delay-oriented scenario

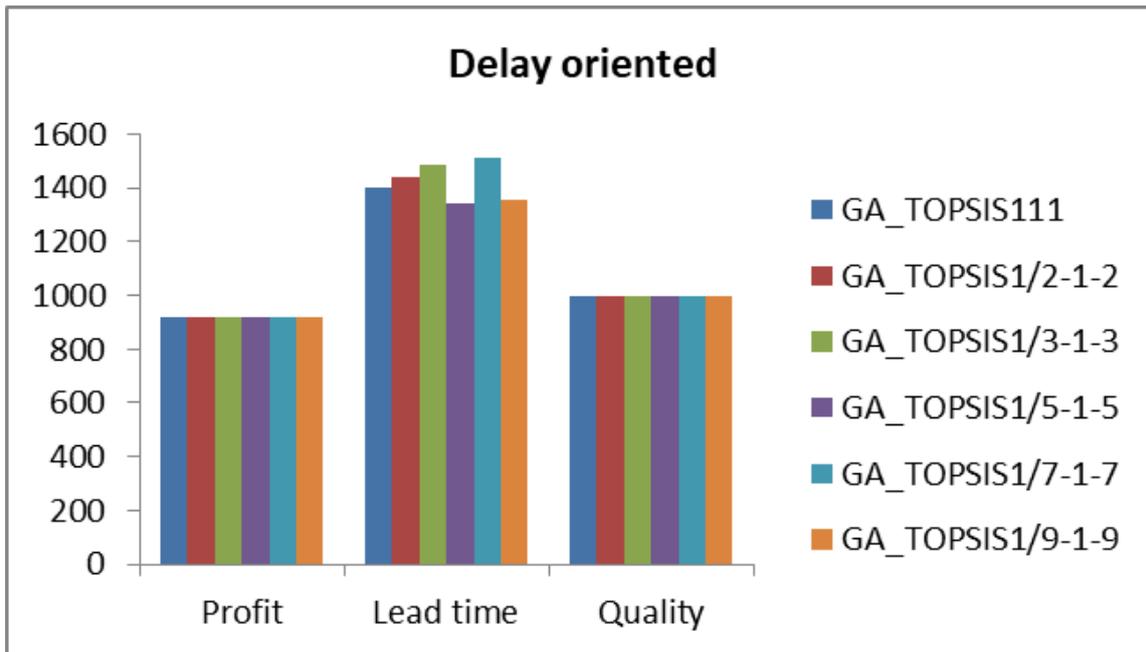


Figure 6.18: Comparison of the best fitness values of the GA-TOPSIS model output parameters for *Delay* oriented scenario

For *Delay* oriented scenario, *Profit*, and *Quality* scores are almost unchanged while *Lead Time* has the unsteady influence both in the positive and negative direction.

Quality-oriented scenario

Quality-oriented configurations, as shown in Figure 6.19, are generated and based on the GA-TOPSIS output for each configuration, the comparison of the best fitness values of the *Profit*, *Lead Time* and *Quality parameters* of the resulted order sequence is shown in Figure 6.20.

Quality oriented	GA_TOPSIS111	GA_TOPSIS1-1/2-1/2	GA_TOPSIS1-1/3-1/3	GA_TOPSIS1-1/5-1/5	GA_TOPSIS1-1/7-1/7	GA_TOPSIS1-1/9-1/9
Profit	918	918	918	918	916	915
Lead time	1404	1441	1446	1496	1369	1359
Quality	1000	1000	1000	1000	1000	1000

Figure 6.19: GA-TOPSIS model outputs for *Quality*-oriented scenario

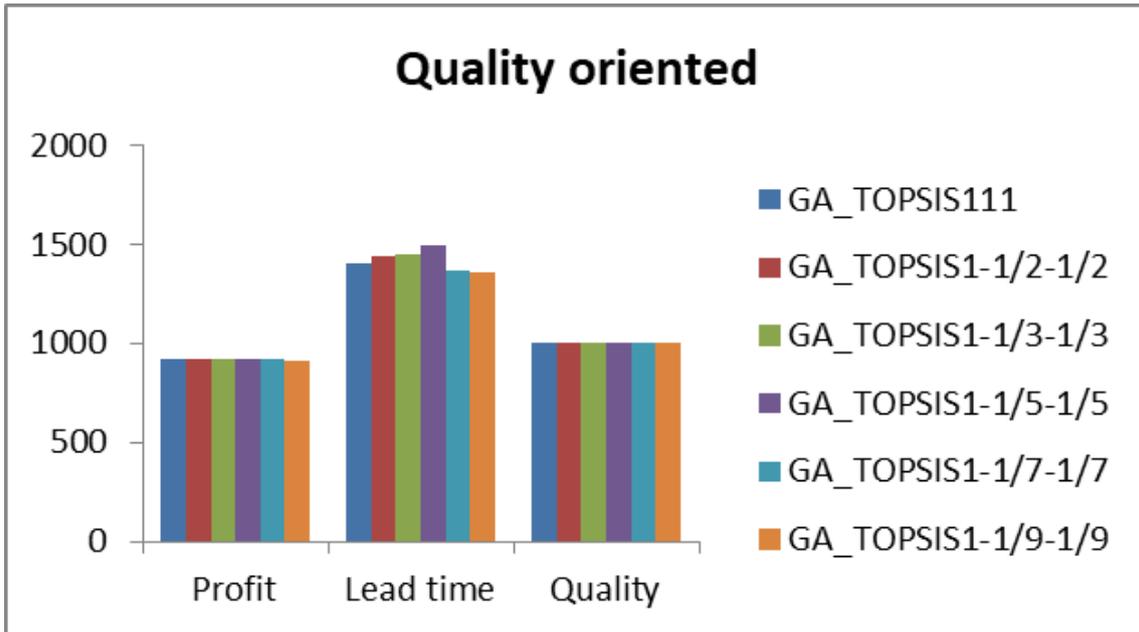


Figure 6.20: Comparison of the best fitness values of the GA-TOPSIS model output parameters for *Quality-oriented scenario*

From Figure 6.20, it can be concluded that the *Lead time* score is increasing for the relatively less degree of importance of *Quality* configuration, and it decreases as the high degree of *Quality* importance.

Cost & Delay oriented scenario

Cost & Delay oriented configurations, as shown in Figure 6.21, are generated and based on the GA-TOPSIS output for each configuration, the comparison of the best fitness value of the *Profit*, *Lead Time* and *Quality parameters* of the resulted order sequence is shown in Figure 6.22.

Cost & Delay oriented	GA_TOPSIS111	GA_TOPSIS122	GA_TOPSIS133	GA_TOPSIS155	GA_TOPSIS177	GA_TOPSIS199
Profit	918	921	1026	1080	1029	1065
Lead time	1404	1603	1600	1617	1539	1511
Quality	1000	971.4285714	885.7142857	828.5714286	800	800

Figure 6.21: GA-TOPSIS model outputs for Cost & Delay oriented scenario

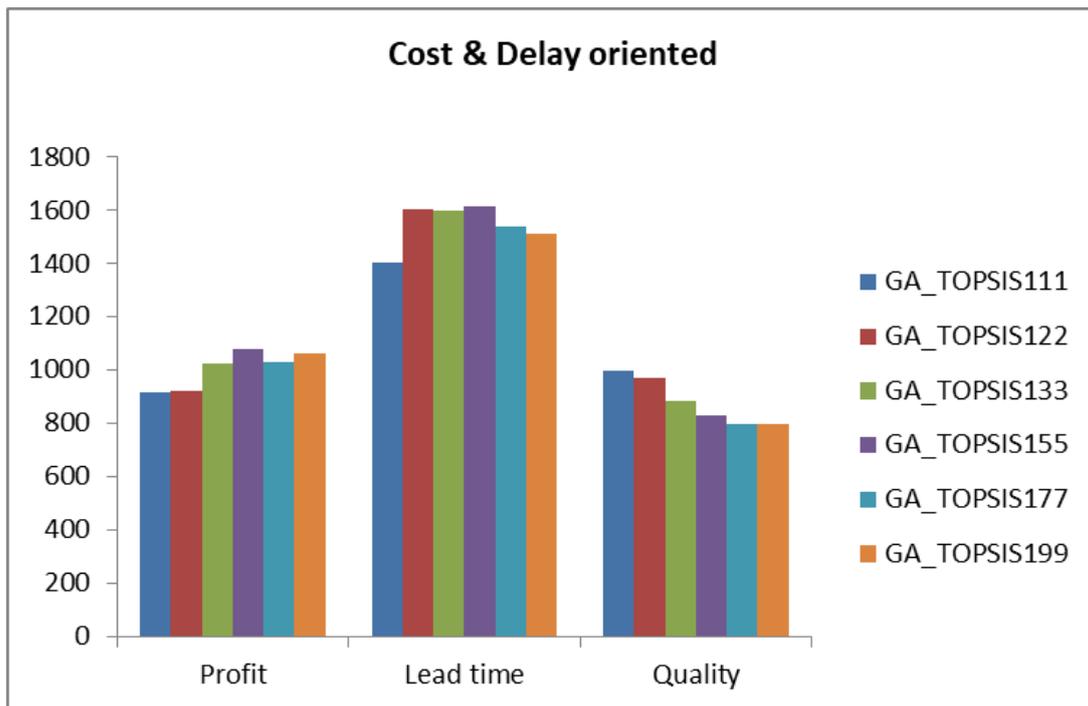


Figure 6.22: Comparison of the best fitness values of the GA-TOPSIS model output parameters for *Cost & Delay oriented scenario*

For a *Cost & Delay oriented scenario*, it can be observed from the Figure 6.22 that the *Profit* and *Quality* exhibit the similar trend as the *Cost oriented scenario* while *Lead time* remains steady for the configurations embedding a middle range of degree of importance of *Cost* and *Delay* criteria over *Quality*.

In summary, the analysis of results obtained in each of the four scenarios presented in this section enables the study of the impact of configurations of the supplier selection criteria evaluations by the decision-makers on the final output of GA-TOPSIS model. This analysis constitutes an effective decision and simulation tool for the small-series fashion supply chain managers to gauge the impact of the trade-off between supplier selection criteria in terms of their relative importance on their business objectives as they process customer orders using GA-TOPSIS model.

6.4 Conclusion

To assign customer orders to the best matching suppliers in a real-time, I applied GA methods that provide the optimal solution for the order assignment problem. In this study, I proposed an evolutionary-GA based approach for customer order assignment in a small-series fashion industry where multiple suppliers participate in providing for the fulfilment of customer orders. Secondly, a hybrid GA-TOPSIS model is applied in order to incorporate a subjective evaluation of the static supplier selection criteria by the decision-makers, similar to the work in Chapter 4. Moreover, as illustrated in Section 6.3.3, different scenarios of configurations of the supplier selection criteria in pairwise comparison manner indicating the top priority criteria of the retailer can be inputted into the GA-TOPSIS model, and the comparison of model results for each configuration enables the retailer to study the impact of such configurations on the profit derived out of each order batch sequence.

By applying GA and GA-TOPSIS methods, the problem of dynamic order assignment to the best garment suppliers is addressed. The static raw material supplier selection problem, addressed in Chapter 4, precedes the RQ3 for which the MCDM method based mechanism is developed. These two mechanisms: 1) static raw material supplier selection; and 2) dynamic order assignment to the best garment suppliers are separate and form the two stages in the small-series fashion supply chain, as illustrated in Chapter 1. As the main data inputs to the GA-TOPSIS method are the customer order data and garment supplier data that entail product and supplier capability features, the dynamic decision scenario applies to the garment supplier selection, unlike static raw material supplier selection. Given the illustrated results in this Chapter, it can be argued that the static raw material supplier selection cannot be replaced by the dynamic garment supplier selection mechanism as the decision context and the data requirements differ for each stage. The production activities of the raw material suppliers are

not directly triggered by the customer orders in real-time, and hence the raw material sourcing decision is static. In contrast, garment manufacturers must respond to the customer orders for the order fulfilment in real-time, which becomes a dynamic decision problem. The major advantage of GA-TOPSIS method for each decision scenario, as illustrated in Section 6.3.3, is that it enhances the dynamic decision making given its ability to take into account the subjective evaluation of the static criteria using Saaty's scale, and the evaluation of the garment suppliers using Likert scale.

GA-TOPSIS based approach is significant as it allows fashion retailers to incorporate their historical judgment of their suppliers into the decision making related to dynamic garment supplier selection problem. In this context, through the experimental study, I demonstrated how the dynamic assignment of each customer order to the best suitable supplier from the pool of participating suppliers in the supply chain could be achieved. Moreover, the GA-TOPSIS results obtained for each scenario presented in Section 6.3.3 contributes to the development of simulation-based decision tool for the supply chain management in small-series fashion. The applied GA and TOPSIS methods-based approach is effective as it could enable retailers to achieve their various objectives while assigning their customer orders to the best suitable suppliers based on both the dynamic and static criteria evaluation together.

Proposed GA and GA-TOPSIS based approach in this chapter contribute to the development of an effective solution for the problem of real-time customer order assignment to the best garment suppliers keeping fashion retailers' objectives in mind. In this way, the study carried out in this chapter addresses the third research question of the thesis (RQ3).

Chapter 7

Conclusion, contributions and future research scope

This thesis starts with the presentation of a systematic literature review that provides a rationale and premise for the research on the basis of identified missing gaps in the literature about the small-series fashion SCM. The cited literature guided the formulation of three research questions that are addressed in this thesis. The outcomes from each research question (RQ1, RQ2, RQ3) are interrelated and contribute as the effective solution that can be applied for solving key supplier selection decision problems in the small-series fashion SCM.

The key contribution and limitation of the study conducted to address each research question are discussed as follows:

- *RQ 1: How the raw material suppliers for small-series fashion production can be selected in supply chains?*

As the study conducted in Chapter 4 is based on real industry case to address RQ1, it serves several valuable managerial insights for the real industrial decision making in small-series fashion SCM. Firstly, decision-makers could utilize the methods presented in Chapter 4 as a decision-making tool to gauge the trade-off between supplier selection criteria in terms of their importance derived from experts' judgements. This way, it is possible to remove less important criteria from the evaluation part and include only those which will be deemed important from the perspective of decision-makers and companies' business goals and needs. Secondly, proposed methods would enable decision-makers to involve a large pool of candidate suppliers for the selection of best among them for the sourcing of raw materials and multiple experts in the decision-making process.

The case study presented in Chapter 4 could serve as the effective analytical tool to solve a static supplier selection problem in a practical industrial scenario where multiple candidate suppliers are willing to provide their raw materials and services for the customized products, and retailers need to decide as to which ones of these candidate suppliers are the best ones as per their business needs and goals. It is worth highlighting that the results from this study have significant managerial implications as they can benefit from a great deal of flexibility in terms of choosing supplier selection criteria as per the retailers' own understanding or discretion, involving multiple candidate suppliers and the decision-makers.

This study has two major shortcomings: firstly, as the decision making in an e-commerce business framework is being increasingly consumer-centric, the consumers could not be directly involved in the criteria and supplier evaluation process; and secondly, common performance indicator could not be developed that will identify the best performing MCDM methods in terms of ranking best suppliers. In future, these limitations can be addressed by exploring opportunities to include product-wise supplier selection aspect in the analysis. Moreover, customer order data attributes could be incorporated in the supplier selection process, which will constitute a big-data oriented approach. Another aspect of future work in this direction could be to develop a larger framework for the easier selection of MCDM method specific to relevant decision-making problems and the agents involved in it.

Another limitation is in terms of addressing the variations in the final supplier ranking when the number of decision-makers is altered in the evaluation process, as has been observed in the model sensitivity analysis results. The crucial problem that could be explored in this respect is to analyze the performance of suppliers selected from single expert evaluation with the ones selected from group evaluation. In future, this aspect can be thoroughly explored, and it can certainly enhance the implications of this study.

- *RQ 2: How the best suitable garment suppliers for the fulfilment of newly arriving customer orders of small-series fashion products can be predicted in a real-time?*

To address RQ2, ML-based approach for the prediction of best garment supplier for a new customer order is implemented in Chapter 5. Through experimental study, it is demonstrated that the ML-based approach is an effective solution for processing customer orders and subsequently for their assignment to the best supplier candidates. The study in Chapter 5 is a novel contribution to solving practical decision problem facing the small- series fashion industry.

The major scope for the improvement in this study lies in the possibility of utilizing more data from the companies. Since the small dataset is used for the analysis, model performance could not be generalized very well. This could be enhanced by collecting large historical customer order dataset. The limitation of this study arising from the relatively lower classification accuracy can be overcome by improving the model parameters according to the features of sales and order datasets. Application of other AI-based models can also be explored while locating the problem of supplier prediction in a broader research context. Moreover, the number of features selected for the prediction of suppliers could be increased depending on the study of the relationship between various market factors and target supplier variable.

- *RQ 3: How the customer orders of small-series fashion products can be effectively sequenced and assigned to the best garment suppliers in a way that it meets the objectives of the retailers and customers?*

RQ3 is addressed in Chapter 6 using GA and GA-TOPSIS model-based optimization approach. The experimental demonstration of the study highlights the significance of the GA based method for solving dynamic customer order assignment problem in the SCM of the small-series fashion industry. Customer order data, supplier data and the business objectives

of the retailers and customers' expectations are all transformed into inputs for GA method, the output of which provides the mechanism for selecting best garment supplier for the specific customer order in a real-time. For GA-TOPSIS method, static and dynamic criteria evaluation by the decision-makers, and supplier evaluation based on these criteria in addition to the customer order data and supplier data are the main inputs. GA-TOPSIS method enables the unique mechanism that allows retailers to feed their historical judgments on their suppliers' performance to the GA-TOPSIS model as inputs. GA-TOPSIS model yields optimum order sequence and best supplier assignment based on all the data inputs.

Real-time order processing is the complex and highly challenging task for small-series fashion retailers since they do not plan their SCM activities beforehand, nor do they base their decisions on demand forecast, unlike traditional fashion SC. Thus, this study is of great importance from the perspective of today's ever-growing needs for efficient industrial solutions to make real-time SCM decisions in the small-series fashion industry.

The limitation of this study is in terms of lack of comparative analysis of applied GA and GA-TOPSIS methods with other hybrid heuristic optimization methods that would help in deciding the best solutions for the order assignment problem. Moreover, in further researches, other important objectives from the small-series fashion retailers' business perspectives can be formulated as input to the models, and the results could be validated using industrial data. Moreover, the scope for achieving raw material supplier selection problem, such as for the fabric suppliers, could be explored by analyzing various data directly from the industry, which could constitute the case-study based approach. It depends on the scale and the growth of the small-series fashion business in the market and the requirement to integrate raw material suppliers into the dynamic decision making. This, however, requires the extensive data collection and analysis for the future development of automated sourcing mechanisms.

- **Overall practical contributions of the thesis**

The aim of the studies conducted in this thesis was to develop an effective decision mechanism for solving key SCM problems in the small-series fashion industry. The current status of researches in the context of research questions addressed in this thesis is very limited. Therefore, this thesis serves to be the stepping stone in the direction of enabling efficient customer order fulfilment mechanism. The proposed methodological approach in this thesis could build the foundation for effective and reliable decision making in the small-series fashion industry as it continues to grow its digital market outreach. The results from the thesis could significantly help SCM experts in the small-series fashion industry to find solutions to the complex decision problems related to supplier selection, customer order management and SC co-ordination. In this way, this thesis lays out the case-based approach that is highly applicable for the business operations of the small-series fashion industry, though they are rapidly evolving due to fierce competitions in the technology and market sectors.

Overall, this thesis research work provides an analytical approach for the assessment of key decision variables from the perspective of suppliers and customers that is crucial for enabling responsive SCM system in the small-series fashion industry. Supply chain managers, who are responsible for making the strategic decisions could benefit greatly from the outputs of this thesis as they would be able to prioritize their business objectives; customer needs and key supplier network co-ordination goals. Although the relatively small data from industry was available, the thesis results constitute the larger methodological framework for solving complex sourcing decisions that small-series fashion industry addresses from a variety of dimensions.

- **Future research scope**

Small-series fashion industry is undergoing rapid transitions due to technological advances and uncertain customer behavior. This rapid transformation adds to the complexity of decision making that what may appear like the easy and linear decision-making process at first. It implies that there will be the ever-growing need for novel researches that will provide practical decision solutions relevant to today's market needs. The research studies conducted in this thesis provide the basis and many opportunities to explore diverse avenues for further research in this context.

One of the major aspects of such an endeavor is to conduct a performance analysis of the proposed methods in real industrial scenarios. It means that the methods need to be applied to extensive industry data that can bring in many decision factors from real SC and production environments. Secondly, other technologies, such as social media could be a potential source of insights into customer preferences that can enhance the efficiency of supplier selection and customer order fulfilment solutions. Social media is a dynamic platform that captures customer choices more than anything else, and it could be utilized for doing raw material sourcing planning in a better manner. This will address the limitation of the study in Chapter 4, where customer insights are not used for selecting raw material suppliers. Moreover, customer survey could also be the possibility of research in this direction, and the inputs can be used for defining key decision criteria for the supplier partnership. Embedding customer insights from social media platforms into analytical decision tools is becoming popular for managing SCM activities.

Finally, emphasis could be given on the study of the impact of product variations on the performance of methods. The generalization and wide validation of the methods depend on their ability to perform in multiple business scenarios.

Appendix I

Chapter 4

SURVEY QUESTIONNAIRE

Participant Company Name- -----
Name of the Decision Maker/Expert- -----
Date: -----

OBJECTIVE- To identify the highly important criteria for selecting the best suppliers for small-series products

Question 1- Keeping the objective in mind, kindly number each of the criteria from the list according to the Likert scale?

<i>Criterion (C)</i>	<i>Type</i>	<i>Number</i>
Cost (C1)	Quantitative	
Market reputation(C2)	Qualitative	
Service efficiency(C3)	Qualitative	
Management efficiency (C4)	Qualitative	
R&D facilities(C5)	Qualitative	
Late delivery(C6)	Qualitative	
Lead time (C7)	Quantitative	
Quality (C8)	Qualitative	
Flexibility (C9)	Qualitative	
Operational efficiency (C10)	Quantitative	
Innovation (C11)	Qualitative	
Trust (C12)	Qualitative	
Location (C13)	Qualitative	
Digitization (C14)	Qualitative	
Sustainability(C15)	Qualitative	

Question 2-

Keeping the objective in mind, kindly rate the relative importance of each criterion with respect to each other

The Scale of Relative Importance

Linguistic description	Numerical value
Equally important	1
Moderately important	3
Strongly important	5
Very strongly important	7
Extremely important	9

Example: According to you, how important is *Cost* with respect to *Lead Time*?

Response- If you think that *Cost* is strongly important than the Lead time, then fill in the value 5 (Strongly Important).

Kindly fill in your responses in the form of numerical values

	Cost	Lead Time	Quality	Flexibility	Operational Efficiency	Innovation	Trust	Location	Sustainable operations
Cost									
Lead Time									
Quality									
Flexibility									
Operational Efficiency									
Innovation									
Trust									
Location									
Sustainable operations									

Appendix II

Academic publications

- Paper titled “Small-series Fashion Supplier Selection using MCDM methods” is selected for the publication in Springer “Multiple Criteria Decision Making Beyond the Information Age: within the Springer’s Book Series Contributions to Management Science (2021)
- Paper entitled “Supplier Prediction in Fashion Industry Using Data Mining Technology” with SebastienThomassey and Xianyi Zeng presented at The 8th International Conference on Industrial Engineering and Systems Management- IESM 2019 (25 – 27 September 2019, Shanghai, China)
- Paper entitled “Supplier Selection in Data-driven Fashion Industry by using MCDM Methods” with SebastienThomassey and Xianyi Zeng presented at the 25th International Conference on Multiple Criteria Decision Making– MCDM 2019 (15 – 21 June 2019, Istanbul, Turkey)
- Paper entitled “Analysis of consumer emotions about fashion brands: An exploratory study” with Chandadevi Giri, SebastienThomassey and Xianyi Zeng presented at 13th International FLINS Conference on Data Science and Knowledge Engineering for Sensing Decision Support-FLINS 2018 (21 – 24 August 2018, Belfast, Northern Ireland, UK)
- Poster entitled “Dynamic Customer Order Management for Customized Fashion Products” presented at the 5th Regional Day for Doctoral Students in Automation Science (3rd July 2018, Amiens, France)

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Titre : Développement d'un système de gestion de la chaîne d'approvisionnement et de la production (SCPMS) de petites séries dans l'industrie de la mode

Résumé : La production en petites séries d'articles de mode est une tendance croissante dans l'industrie de la mode car elle permet, entre autres, aux clients de personnaliser leurs propres produits tels que des vêtements, des articles de mode de luxe, etc. Cette tendance se traduit par le besoin toujours croissant d'une gestion efficace de la chaîne d'approvisionnement (SCM) qui constitue un des facteurs clés du succès de la production en petites séries. Cependant, les modèles SCM existants ne parviennent pas à répondre aux besoins et aux problèmes de la chaîne d'approvisionnement en petites séries notamment en termes de résolution des problèmes décisionnels complexes liés à la sélection des fournisseurs, à la coordination de la chaîne d'approvisionnement et à la gestion dynamique des commandes clients. Pour combler ces lacunes, cette thèse propose une approche scientifique pour développer une méthode d'aide à la décision efficace pour la gestion de la chaîne d'approvisionnement de la mode en petites séries. L'objectif principal de cette thèse est de développer des solutions d'aide à la décision efficaces pour gérer les problèmes de décision clés dans la gestion de la chaîne d'approvisionnement de la mode en petites séries en s'appuyant sur des études expérimentales. Sur la base d'une revue systématique de la littérature de l'industrie de la mode en petites séries et des modèles de gestion de la chaîne d'approvisionnement, trois questions de recherche sont formulées en fonction des lacunes identifiées dans la littérature. Ces questions de recherche constituent les axes de développement significatifs de la gestion de la chaîne d'approvisionnement de la mode en petites séries. La première question de recherche porte sur la sélection des fournisseurs de matières premières de manière statique basée sur les méthodes d'aide à la décision multi critères. La deuxième question de recherche explore le problème de la meilleure prédiction des fournisseurs pour les nouvelles commandes de clients d'articles de mode en petites séries basées sur des méthodes d'apprentissage automatique. La troisième question de recherche développe un algorithme génétique et un mécanisme basé sur la méthode TOPSIS pour l'attribution dynamique des commandes clients aux fournisseurs de vêtements les plus appropriés selon des critères à la fois quantitatifs et qualitatifs. Les résultats démontrés dans cette thèse fournissent des informations managériales importantes pour aider les entreprises de mode basées sur une production en petites séries à résoudre des décisions complexes de SCPM.

Mots-clés : *production en petites séries, industrie de la mode, gestion de la chaîne d'approvisionnement, sélection multi critères des fournisseurs, gestion dynamique des commandes clients, personnalisation.*

Title: Development of the Supply Chain and Production Management System (SCPMS) for Small-series Fashion Industry

Abstract: Small-series fashion production is a popular and growing trend in the fashion industry as it enables customers to customize their fashion products such as garments, fashion luxury items, etc. This trend translates into the ever-growing need for efficient supply chain management that constitutes the backbone of the small-series fashion industry. However, the existing SCM models fail to address the needs and the problems of the small-series supply chain in terms of solving complex decision problems related to supplier selection, supply chain co-ordination and dynamic customer order management. Therefore, this thesis proposes a scientific approach for the development of an effective mechanism to aid the decision making in the small-series fashion supply chain management. The main objective of the research conducted in this thesis is to develop decision-support solutions for managing key supply chain management decision problems. Based on the systematic literature review of the small-series fashion industry and supply chain management models, three research questions are formulated that are guided by the identified gaps in the literature. These research questions constitute the significant aspects of the small-series fashion supply chain management. The first research question addresses the raw material supplier selection in a static way. The second research question explores the problem of best supplier prediction for new customer order of small-series fashion items. The third research question focuses on the processing of continuously arriving customer orders by dynamically assigning them to the best suppliers. The methodology used in this thesis is based on the combination of techniques: MCDM methods; Machine learning; and the Genetic Algorithm.

Keywords: *small-series fashion, supply chain management, customization, supplier selection, customer order management*