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LEVERAGING SUPPLIER SELECTION WITHIN SUPPLY CHAIN MANAGEMENT UNDER UNCERTAINTY

THOMY EKO SAPUTRO
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Leveraging Supplier Selection Within Supply Chain Management Under Uncertainty

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Abstract

Supplier selection is one of the vital purchasing activities that has an integrative role in the firms' strategic planning process. It should align with the purchasing strategy so that goals can be achieved successfully. The need to manage the supply of different types of purchased items with differentiated strategies has been recognized as their contributions and profit impacts, as well as supply complexity. Kraljic's portfolio matrix has been widely used as a tool to classify items and develop purchasing strategies. In this context, each stage of the supplier selection process, including problem definition, identification of criteria, and final selection, requires a framework that aligns with the purchasing strategy.

Purchasing managers' biggest challenge to deal with the items representing high supply complexity is mitigating risks that potentially emerge from suppliers, such as delivery delay, quality problems, and supply disruptions. The failures due to these risk factors can lead to a significant monetary loss, particularly for the items that have a significant impact on profit. Therefore, supplier selection of these strategic items is not straightforward. It requires careful considerations within supply chain management to help firms maintaining the continuity of supply efficiently and gain competitive advantages. Not all these critical issues have been well addressed in supplier selection studies, and a proper framework linking with the purchasing strategies has not been formalized and linked to the purchasing strategies while selecting suppliers has not been formalized.

Motivated by Kralijc's portfolio matrix and production policy, this dissertation aims to develop a supplier selection framework and accordingly propose models for supplier selection of strategic items, appropriately incorporating all the key features. This is achieved by conducting a comprehensive literature review on supplier selection, which assists in linking strategic drivers with formulations and approaches, and highlights trends and directions for future research. In addition, new models and approaches are proposed, focusing on the integration of supplier selection and inventory management, and incorporating different types and sources of uncertainty.

This dissertation can therefore provide useful technical guidance for practitioners and academia to address the relevant areas of study in operation and supply chain management. In addition, some managerial insights present important notes of decision-making under multi-criteria.

Resumo

A seleção de fornecedores é uma das atividades vitais de compras que tem um papel integrador no processo de planejamento estratégico das empresas. Deve estar alinhado com a estratégia de compras para que os objetivos possam ser alcançados com sucesso. A necessidade de gerenciar o suprimento dos diferentes tipos de itens comprados com estratégias diferenciadas tem sido reconhecida por suas contribuições e impactos nos lucros, bem como pela complexidade do fornecimento. A matriz de portfólio da Kraljic tem sido amplamente utilizada como uma ferramenta para classificar itens e desenvolver estratégias de compra. Nesse contexto, cada etapa do processo de seleção de fornecedores, incluindo a definição do problema, a identificação dos critérios e a seleção final, requer uma estrutura que se alinhe à estratégia de compras.

O maior desafio dos gerentes de compras para lidar com os itens que representam alta complexidade de fornecimento é mitigar riscos que potencialmente emergem dos fornecedores, como atraso na entrega, problemas de qualidade e interrupções no fornecimento. As falhas devido a esses fatores de risco podem levar a uma perda monetária significativa, principalmente para os itens que têm um impacto significativo no lucro. Portanto, a seleção de fornecedores desses itens estratégicos não é simples. Requer considerações cuidadosas no gerenciamento da cadeia de suprimentos para ajudar as empresas a manter a continuidade do fornecimento de forma eficiente e obter vantagens competitivas. Nem todas essas questões críticas foram bem tratadas nos estudos de seleção de fornecedores, e uma estrutura adequada vinculando as estratégias de compra não foi formalizada e vinculada às estratégias de compra durante a seleção dos fornecedores.

Motivada pela matriz de portfólio e pela política de produção da Kralijc, esta dissertação tem como objetivo desenvolver uma estrutura de seleção de fornecedores e, consequentemente, propor modelos para a seleção de fornecedores de itens estratégicos, incorporando de forma adequada todas as principais características. Isso é obtido por meio da realização de uma revisão abrangente da literatura sobre a seleção de fornecedores, que auxilia na vinculação dos direcionadores estratégicos às formulações e abordagens e destaca tendências e direções para pesquisas futuras. Além disso, novos modelos e abordagens são propostos, com foco na integração da seleção de fornecedores e gestão de estoque, e incorporando diferentes tipos e fontes de incerteza.

Esta dissertação pode, portanto, fornecer orientação técnica útil para profissionais e acadêmicos para abordar as áreas de estudo relevantes na operação e gestão da

cadeia de abastecimento. Além disso, alguns insights gerenciais apresentam notas importantes sobre a tomada de decisões segundo critérios múltiplos.

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Chapter 1
Motivation and Overview

In today's global market, competition among firms in different industries becomes more intense. That compels firms to improve their inbound and outbound processes in the supply chain to stay competitive. Nowadays, purchasing plays a vital role in the inbound process of a supply chain. It is recognized as a strategic concern that enables firms to efficiently manage the material flow within the supply chain and determine supply, production, and distribution planning (Nair et al., 2015). A firm's ability to manage purchasing has been empirically associated with the contribution to the competitive advantages (Montgomery et al., 2018).

Purchasing has a vital function for firms to strategically acquire materials and services, fostering the ability to meet their customer's needs. One of the critical challenges confronted by purchasing managers is selecting strategic suppliers that provide them with the required products, components, and materials in a timely and effective manner so that competitive advantages can still be maintained.

The strategic approach for purchasing functions differs for each purchasing classification (a type of purchased parts or items), such as introduced by Kraljic (1983) classifying it based on the profit impact and supply risk. Therefore, selecting suppliers according to the right purchasing strategy is essential to the entire supply chain.

1.1 Purchasing Classification

In an effort to improve performance of firms in dealing with purchasing operations, all purchased materials should not be managed in the same way (Gelderman and Weele, 2003). It requires differentiation and some sort of classification of these purchases (Gelderman and Weele, 2003). Purchasing portfolio models have developed to provide an approach for differentiating purchasing.

Kraljic (1983) introduced the first portfolio matrix classifying purchased items based on the importance of purchasing and complexity of supply. The importance of purchasing is evaluated based on product quality impacts, business growth, and profit impacts. Supply of items is considered complex when the availability and number of suppliers are scarce, as it triggers a risk of supply. In addition, the complexity of supply can also be assessed in terms of competitive demand, make-or-buy opportunities, storage risks, and substitution possibilities. Figure 1.1 shows purchasing classification according to Kraljic portfolio matrix (KPM).

According to the KPM, there are four different types of items, which are described in the following:

- **Strategic Critical items** represent high-profit impacts and high supply risks. Supply management is an appropriate strategy to manage critical items. In turn, a strategic procurement initiative must be designed to minimize total cost and reduce supply risk successfully. In order to decide on critical items, the involvement of cross-functional teams from the top-level management is needed. Information regarding a long-term supply and demand trend is needed in order to pursue the success of supply management implementation. The time horizon of purchase planning is very long and can reach up to 10 years.

- **Non-critical items** are regarded as the items whose importance of purchasing and supply risk are low. The decision-making of these items is decentralized, which is represented by lower-level management teams. Suppliers can be local with short-term relationships. The horizons of purchase planning for these items are generally under one year.

- **Leverage items** indicate high-profit impacts with low supply risks. The main focus of managing the supply of leverage items is to prevent monetary losses through a pricing strategy and contract negotiation. Material management is a strategy that can be applied to manage these items. A short-term up to medium-term demand planning is a suitable undertaking for materials management implementation. The time horizon for purchase planning these items usually is 12 to 24 months.

- **Bottleneck items** would impact insignificantly on profit, but it massively impacts on the operation. It is essential to focus on cost management and medium-term sourcing planning under a long-term contract. The purchase time horizon are managed depending on the availability of items.

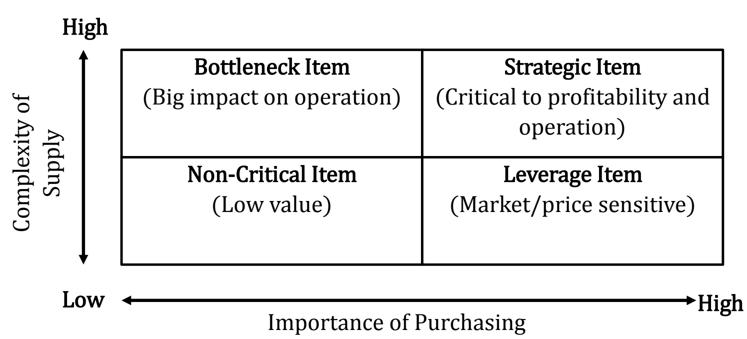

Figure 1.1: Purchasing classification (Kraljic, 1983)

KPM has been widely used as a diagnostic and prescriptive purchasing tool

(Montgomery et al., 2018). For instance, it has been used to classify and position purchased items in areas such as public procurement (Padhi et al., 2012), construction (Ferreira et al., 2015), and manufacturing (Lee and Drake, 2010), as well as to analyze supplier selection methods (de'Boer et al., 2001).

1.2 Supplier Selection

Supplier selection is one of the most important purchasing activities, as companies' performance and competitive advantages rely on the collaboration with capable suppliers (Wagner, 2006). More specifically, suppliers contribute to the four main competitive priorities, namely quality, delivery, flexibility, and cost (Prajogo and Olhager, 2012). In general, the cost of materials and components, particularly for high technological products, can range from 60% to 80% of production cost (Dey et al., 2015). Selecting appropriate suppliers and carrying out their involvement to assist strategic supply management activities can reduce material cost and product development time by 20% and improve material quality by 20% (Monczka et al., 2015). Clearly, supplier selection is critical to the overall firm's performance.

However, selecting appropriate suppliers is not a straightforward process. It relies not only on the selection (solution approach) itself but also on the precedent phases, including the problem definition and the criteria identification (de'Boer et al., 2001).

Due to their different degrees of complexity and importance, the supplier selection process must be specific for different types of items. This is evident that supplier selection requires an appropriate framework addressing each phase of the decision-making process. KPM can be useful as a starting point for developing a supplier selection framework, particularly in defining the selection problem and identifying criteria according to the supply complexity and purchasing importance, which in turn, can align with the purchasing strategies and firm's goals. Despite the vast literature on supplier selection, there is not a comprehensive framework underlying the supplier selection process that addresses these concerns, linking to purchasing strategies.

The strategic role of supplier selection becomes important for the purchase of items whose financial impact and supply complexity are high (e.g., chipsets in the electronic industry). Supplier selection for these strategic items should therefore be the focus of any organization. It requires a comprehensive process, considering other related activities in a supply chain in order to reduce costs, as well as to improve the other aforementioned competitive priorities (quality, delivery, flexibility). By contrast, this decision should not be as critical for low-cost items with abundant sources (e.g., standard screws in the electronic industry). For these non-critical items the main focus is to simplify procurement processes and make day-to-day purchases, whereby supplier selection is expeditious (Monczka et al., 2015).

A supplier selection process typically deals with an evaluation of several alternatives under multi-criteria (i.e., cost, quality, delivery, and flexibility). Due to conflicting nature of the criteria for selecting the best supplier, the criteria need to be traded off. Under multiple (conflicting) criteria, supplier selection requires a careful decision-making process, which is most likely to be complex in nature. In practice, evaluating suppliers under multiple criteria is typically performed based on decision-makers' judgment (DMs). It can lead to vague judgment when the exact value of the evaluated alternatives is not available. In this uncertain decision environment, DMs' opinions or judgments need to be perceived realistically to avoid potentially misleading decision-making. Handling this uncertainty cannot be simply performed. It requires transforming linguistic variables into uncertain numerical values (Haeri and Rezaei, 2019).

Furthermore, the complexity of supply and rapid change of the global market have compelled companies to focus on risk mitigation. Some of the potential supply risks might come from suppliers due to delivery failure, quality problem, discontinuity of supply, or disruptions (Zsidisin, 2003). Disruptions are phenomena which are very difficult to predict and avoid, but their risks can be mitigated. Severely, supply processes can be entirely forced to shut down due to massive disruption and firms will lose business competitiveness as customer demand cannot be appropriately fulfilled. Therefore, the ability of suppliers to recover from its impact is very significant to the supply.

Building supply chain resilience, as well as mitigating supply risk is not trivial. An effort can be made by redesigning supplier selection processes. For instance, the adoption of risk factors into selection criteria (Awasthi et al., 2018; Igoulalene et al., 2015; Rajesh and Ravi, 2015) and multi-sourcing (Haleh and Hamidi, 2011), as well as integrating with inventory management (Firouz et al., 2017; Keskin et al., 2010) become the major focus for risk mitigation in the related areas of supplier selection.

A number of studies on supplier selection have been presented considering uncertainty (Ayhan and Kilic, 2015; Cheraghalipour and Farsad, 2018; Gören, 2018; Guo and Li, 2014; Hamdan and Cheaitou, 2017; Hlioui et al., 2017; Jain et al., 2015; Kilic and Yalcin, 2020; Singh, 2014; Zarindast et al., 2017) and risks (Awasthi et al., 2018; Firouz et al., 2017; Igoulalene et al., 2015; Keskin et al., 2010; Rajesh and Ravi, 2015). Yet, some aspects still need further improvement, particularly to deal with uncertain supplier-buyer related parameters (such as quality and delivery) and DM's judgment. Redesigning supplier selection processes for mitigating risks of strategic items needs to be integrated with other dimensions (sourcing strategy, criteria, and scope) since none of the studies have been concerned with this implementation. Thus, tackling the key features of the problem using distinguished solution approaches is imperative.

1.3 Research Objectives

This study focuses on supplier selection for strategic items. The main objective of this study is to provide such a framework, from which we are able to devise approaches for different settings. This study also focuses on addressing supplier selection based on a comprehensive decision-making process using an effective solution approach dealing with uncertainty and supply risks. Accordingly, this study comprises four main research questions shown in Figure 1.2 as follows.

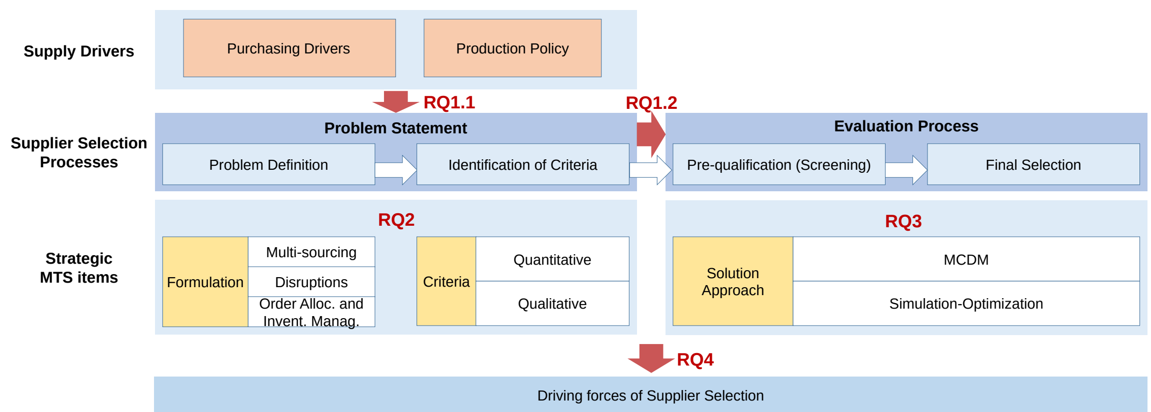

Figure 1.2: The structure of research questions

RQ1: How should supplier selection be approached in general?

- RQ1.1: How should supplier selection be formulated for different types of items and production policies?
- RQ1.2: How should a given supplier selection problem statement (formulation) be approached?

This research question holds two main objectives, which indicated in Figure 1.2. First, we identify key dimensions in each stage of the supplier selection process and determine the dimensions based on the purchasing drivers (associated with KPM) and production policy so that supplier selection problem can be appropriately formulated. Second, we analyze different supplier selection approaches and formalize the appropriate ones for the respective problem to address the dimensions.

RQ2: How can supplier selection for strategic items be modelled ?

We fill the gaps in the existing literature by addressing a comprehensive supplier selection problem for strategic items and developing suitable models aligned with the supplier selection framework. The models incorporate all key features, including uncertainty and supply risks (e.g., disruptions, imperfect quality, and delivery delay), to properly address the main competitive priorities and the design of supply risk mitigation strategies.

RQ3: How can supplier selection models for strategic items be solved?

First, we promote the development of a simulation-optimization (S-O) method focused on a complex problem in order to efficiently and effectively address the issues arising from uncertainty and supply risk. This solution approach allows the design of disruption mitigation strategy through enhancing inventory decisions, as well as implementing multi-sourcing. Second, we develop a novel two-phase solution approach using hybrid MCDM and multi-objective simulation-optimization to solve the proposed model, addressing different sources of uncertainty.

RQ4: What are the driving forces of supplier selection?

We identify the driving forces of supplier selection synthesized from the literature review that become key to supplier selection in contributing competitive advantages and fostering their supply chain. This points to different research avenues.

1.4 Research Outline

The main chapters of this dissertation comprise several papers aiming at answering the research questions indicated in the previous section. Chapter 2 is presented to address RQ1 and RQ4. Chapters 3 and 4 address RQ2 and RQ3. Chapter 3 contributes to a published paper (Saputro et al., 2020) which is developed according to the work published in a proceeding journal (Saputro et al., 2019). The remainder of this dissertation is organized as follows.

Chapter 2 provides a state-of-the-art literature review on supplier selection problems. More specifically, it provides an exploratory review to discuss each of the main dimensions that characterize the problems, including sourcing strategy, decision scope, decision environment, selection criteria, and solution approach. This chapter introduces a methodology used to answer the first primary research question, including the novel framework that we extend from the literature to guide the research process. At the end of this chapter, the discussion of the problem statement and approach for different types of items is presented.

In Chapter 3, a supplier selection model and solution approach are proposed to contribute to the second and third research questions, respectively. This model addresses the integration of supplier selection and inventory management under supply disruptions, incorporating imperfect quality and carrier capacity, as well as their associated costs. A review system (Q, R) is adopted in the model. We also contribute a novel solution approach for supply risk mitigation using the output of simulation to refine an affected parameter so that a given analytical model can be enhanced, the so-called analytic model enhancement (AME).

Chapter 4 provides an extensive model and solution approach to deal with supplier selection under multi-criteria evaluation. The proposed model also addresses the inherent uncertainty to accommodate more realistic DMs' judgment and accurate supplier-buyer related parameters. We develop a novel two-phase solution approach using hybrid MCDM and simulation-optimization to solve the proposed model.

Chapter 5 emphasizes the key concern from this research and explicitly answer the stated research questions. Additionally, managerial insights derived from the analysis of the studies and the directions for future research are presented.

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Chapter 2

A Novel Supplier Selection Framework

A Comprehensive Framework and Literature Review of Supplier Selection Under Different Purchasing Strategies

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Abstract Supplier selection has received substantial consideration in the literature since it is considered one of the key levers contributing to a firm's success. Selecting the right suppliers for different product items requires an appropriate problem framing and a suitable approach. Despite the vast literature on this topic, there is not a comprehensive framework underlying the supplier selection process that addresses those concerns. This paper formalizes a framework that provides guidance on how supplier selection should be formulated and approached for different types of items segmented in Kraljic's portfolio matrix and production policies. The framework derives from a thorough literature review, which explores the main dimensions in supplier selection, including sourcing strategy, decision scope and environment, selection criteria, and solution approaches. Over 150 papers, published from 2000 to 2020, were reviewed for said purpose. The results indicate that supplier selection regarding items with a high purchasing importance should lead to holistic selection criteria. In addition, items comprising a high complexity of supply and production activities should require integrated selection and different sources of uncertainty associated with decision scope and environment, respectively to solve it, as well as hybrid approaches. There are still many research opportunities in the supplier selection area, particularly in the integrated selection problems and hybrid solution methods, as well as in the risk mitigation, sustainability goals and new technology adoption.

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Keywords: Supplier selection, Kraljic portfolio matrix, literature review, sourcing strategy

2.1 Introduction

Selecting appropriate suppliers and carrying out their involvement to assist strategic supply management activities can reduce material costs and product development time by 20% and improve material quality by 20% (Monczka et al., 2015). Clearly, supplier selection is critical to the overall firm's performance. However, selecting appropriate suppliers is not a straightforward process. It relies not only on the selection (solution approach) itself but also on the precedent phases, including the problem definition and the criteria identification (de'Boer et al., 2001).

The strategic role of supplier selection becomes important for the purchase of items whose financial impact and supply complexity are high (e.g., chipsets in the electronic industry). By contrast, this decision should not be as critical for low-cost items with abundant sources (e.g., standard screws in the electronic industry). Due to their different degrees of complexity and importance, the supplier selection process must be specific for different types of items. Kraljic (1983) introduced the first portfolio model for segmenting purchases. The author has identified four classes of items (non-critical, leverage, bottleneck, and strategic), based on two dimensions: supply risk (complexity) and the purchase importance (shown in Figure 1.1). The Kraljic Portfolio Matrix (KPM) has been widely used as a diagnostic and prescriptive purchasing tool (Montgomery et al., 2018). For instance, it has been used to classify and position purchased items in areas such as public procurement (Padhi et al., 2012), construction (Ferreira et al., 2015), and manufacturing (D. M. Lee and Drake, 2010), as well as to analyze supplier selection methods (de'Boer et al., 2001). It has received considerable attention since the firm's ability to manage supplier relations empirically linking to competitive advantages has been recognized (Montgomery et al., 2018). Furthermore, KPM can also be useful as a starting point for developing a supplier selection framework, particularly in defining the selection problem and identifying criteria according to the supply complexity and purchasing importance.

It is worth of note that various industries differ in the production policy used to meet their demand, such as make-to-stock (MTS), assembly-to-order (ATO), make-to-order (MTO), and engineer-to-order (ETO). Accordingly, their competitive priorities and operational performance outcomes may also differ (Olhager and Prajogo, 2012). For instance, MTS (make-to-stock) companies typically compete on price and cost efficiency, while MTO (make-to-order) companies compete on customization and flexibility. Thus, to sustain strategic competitive priorities, companies should cooperate with the right suppliers. In other words, supplier selection criteria and framework must be in accordance with the competitive priorities of the respective production policy.

A number of literature reviews on supplier selection has been presented. The majority is focused on identifying trends and potential solution approaches for supplier selection (Chai, J. N. Liu et al., 2013; Chai and Ngai, 2020; Karsak and Dursun, 2016; Simić et al., 2017). Other reviews have also delved into the selection criteria (Ho et al., 2010; Mukherjee, 2016; Wetzstein et al., 2016), and some focused their analysis on green and environmental contexts (Govindan, Rajendran et al., 2015; Igarashi et al., 2013; Zimmer, Fröhling and Schultmann, 2016). The discussion of other dimensions in supplier selection, such as sourcing strategy and uncertainty environment, has also been conducted, but in specific contexts or for specific methods (e.g., Aissaoui et al. (2007) considered those two additional dimensions when evaluating mathematical programming approaches). While the existing literature is helpful to provide the principles for identifying supplier selection criteria and methods, as well as to understand the decision environment, analysis of the supply chain activities integrated with supplier selection (decision scope) has not been discussed. Furthermore, a framework that integrates these dimensions and links to critical drivers (such as KPM and production policies) has not been presented.

This paper provides such a framework, from which we are able to derive insights into supplier selection problems. Accordingly, this paper aims to contribute to the literature in four important ways. First, we expand preceding literature by providing an updated and comprehensive review of supplier selection papers that is deeper and broader than prior reviews. Second, we link the reviewed papers to the KPM and production policy, therefore understanding how supplier selection should be formulated in different contexts. Third, we connect the different supplier selection dimensions to identify the right approach to each setting. Fourth, we extract existing research gaps and synthesize research recommendations to direct future avenues of research. We aim at answering three main research questions:

- (**Q1**) How should supplier selection be formulated for different types of items and production policies?
- (**Q2**) How should a given supplier selection problem formulation be approached?
- (**Q3**) What are the research trends and opportunities for supplier selection?

The remainder of the paper is organized as follows. Section 2 presents the methodology used to answer the three research questions, including the novel framework that we extend from the literature to guide the research process. Section 3 provides an exploratory review in each of the main dimensions that characterize this problem. The first two research questions are then explored in Section 4. Finally, we highlight the findings, as well as recommendations for future work in Section 5.

2.2 Research Methodology

A synthesis of supplier selection studies reveals the main dimensions found to influence the diversity and complexity of decision–making in this context. Those dimensions include: sourcing strategy (Aissaoui et al., 2007; de'Boer et al., 2001), decision environment (Chai and Ngai, 2015), decision scope (Nair et al., 2015), supplier selection criteria (Govindan, Rajendran et al., 2015; Ho et al., 2010), and solution approaches (Chai and Ngai, 2020; de'Boer et al., 2001).

To answer the research questions previously presented, we extend de'Boer's framework (de'Boer et al., 2001) of supplier selection by considering the dimensions identified, and by connecting them to the KPM and production policy that characterize each type of items. Our framework is depicted in Figure 2.1.

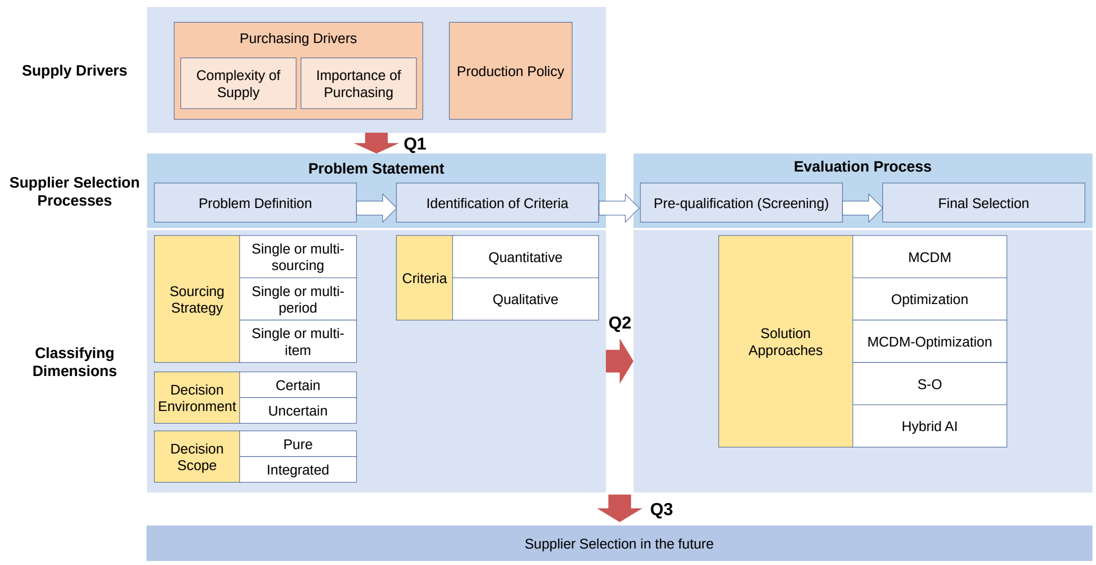


Figure 2.1: A framework of supplier selection (adapted from Aissaoui et al. (2007) and de'Boer et al. (2001)) and context of the study

According to this framework, this study comprises two fundamental questions (Q1 and Q2) associated with two phases of the supplier selection process, namely problem statement and the evaluation. The focus of Q1 is to represent a thorough problem statement in the context of purchasing management. Thus, we investigate an appropriate sourcing strategy, decision scope and environment, as well as selection criteria associated with the different types of items and production policies. According to these dimensions, Q2 is then addressed to examine a suitable approach to that problem. Finally, and based on all the reviewed papers, driving forces of supplier selection are disclosed (Q3) to explore research opportunities synthesized from the literature.

This review addresses the studies of supplier selection from over 150 articles collected from the scholarly published journal between 2000 and 2020. There is a higher focus on papers published in the last 10 years since recently published reviews covered those published until 2012 (Chai, J. N. Liu et al., 2013; Govindan, Rajendran et al., 2015; Igarashi et al., 2013; Mukherjee, 2016). The papers have been published online and publicly available on digital databases, including Elsevier's Science Direct, Springer, Taylor & Francis, Emerald Publishers, Inderscience, IEEE Xplore, and Wiley Online Library.

To establish a reproducible and unbiased article search process, the following keywords were used: supplier selection, supplier evaluation, vendor selection, vendor evaluation, supplier integration, vendor integration.

2.3 Exploratory Review: The Dimensions of Supplier selection

We present the review according to the dimensions of supplier selection shown in Figure 2.3. The review is systematically organized according to the following order. First, we provide an overview of the sourcing strategy that has been implemented in various industries, discussing sourcing strategy associated with the number of selected suppliers (single or multi-sourcing), planning horizon (single or multi-period demand planning), and the number of items (single or multi-item). Second, we discuss the decision scope in supplier selection problems (pure and integrated selection). Third, we analyze the decision environment, categorized as certain or uncertain. Fourth, we identify the selection criteria, and, finally, we the studies according to the solution approaches are reviewed.

2.3.1 Sourcing Strategy

There are two types of sourcing strategies, namely single and multi-sourcing, and both can be used regarding single or multi-item, as well as single or multi-period. In this review, we discuss sourcing strategies according to the number of suppliers, items, and period, which is illustrated in Figure 2.2.

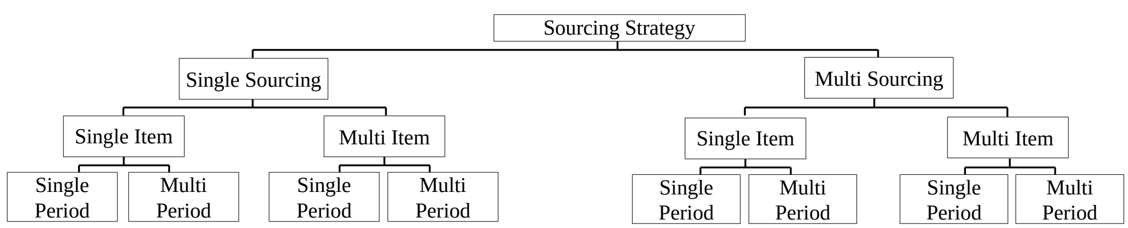


Figure 2.2: Categories of sourcing considered in supplier selection problems

86% of the studies focus on a multiple sourcing strategy and the remaining 14% deal with a single sourcing strategy. According to the number of items, the amount of studies addressing single and multi-item are 44% and 56%, respectively. Most of the studies (54%) consider long term demand planning, which is aggregated into a single-period model. On the other hand, 46% of the studies cover a multi-period model.

According to the planning horizon, a single-period supply indicates that the amount of items to be purchased (order quantity) is constant (non-dynamic), and selected suppliers are identical within the planning period. By contrast, multi-period supply implies a dynamic setting where the number of suppliers and selected suppliers is non-identical, depending on the demand in each period. The order quantity would change over time as a result of dynamic demand. Generally, a multi-period model indicates demand planning with short time window (i.e., weekly or monthly) (Choudhary and R. Shankar, 2014; Jafari Songhori et al., 2011). Conversely, a single-period model most likely involves demand planning with large time window (i.e., yearly) (S. Ghodsypour and O'Brien, 2001; Kull and S. Talluri, 2008).

In multi-sourcing settings, orders generally need to be adequately allocated to each supplier without omitting its capacity. Managing the supply under multi-sourcing can be complicated in terms of multi-item (Che, 2010a; Rezaei and Davoodi, 2008).

2.3.2 Decision Scope

According to the scope, supplier selection problems can be classified into two major categories, namely pure and integrated selection. The latter involves not only supplier selection but also other supply chain related activities such as order allocation, transportation, inventory management, production planning, and closed-loop supply chain or reverse logistics (as shown in Figure 2.3). Despite the integrated selection accounting for 77% of the papers, most of the studies only integrate supplier selection with order allocation. In fact, integrated problems considering vehicle selection (4%) , inventory management (20%), production planning (6%), and material flows in reverse logistics (8%) are still scarcely studied.

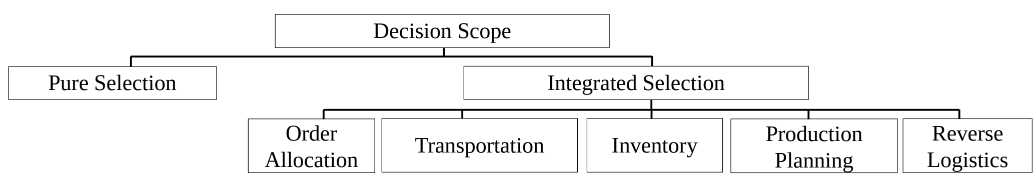


Figure 2.3: Categories of decision scope in supplier selection problems

2.3.2.1 Pure Selection Problems

Pure selection involves a single type of decision: selecting or ranking the best supplier. The selection process generally follows a decision-making framework that relies on decision-maker judgment. It typically involves evaluation processes that are initialized by defining the problem, identifying criteria, and determining the criteria' relative importance (criteria weighting). In other words, the final selection output can stem from either a “yes" or “no" decision or a continuous supplier scoring system.

Typically, the scope of pure selection depicts the implementation of a single-sourcing strategy, for a single-item, and within a single-period (Bai et al., 2019; Bruno et al., 2012; Ghoushchi et al., 2020; Gupta and Barua, 2018). Nevertheless, it is still possible to source from the desired number of suppliers according to the decision-makers' (DM) perspectives, although the optimal number of the selected suppliers is not guaranteed.

A case study of supplier selection based on the pure selection has been carried out in manufacturing companies engaged in computer, communication, and consumer electronics ("3C") products (Chai and Ngai, 2015), public road and rail transportation (Bruno et al., 2012; Dulmin and Mininno, 2003), electronics (Gao et al., 2020; D. Kannan, Govindan et al., 2015; A. H. Lee, Kang, Hsu et al., 2009; Rajesh and Ravi, 2015), automobiles (Awasthi and G. Kannan, 2016; Hashemi et al., 2015; Memari et al., 2019; Sanayei, Mousavi et al., 2010), textiles (Guarnieri and Trojan, 2019; Y. Li et al., 2020), wood & paper (Valipour Parkouhi et al., 2019), energy (Lu et al., 2019), and constructions (Matic et al., 2019). These studies applied a decision-making process that normally relies on decision-makers' judgment. The decision-makers played a key role in identifying supplier selection criteria that meet company strategies and needs, as well as assessing potential suppliers. The strategic decisions were taken by determining the ranking of suppliers according to their performance score and deciding on the number of suppliers to be selected.

2.3.2.2 Integrated Selection Problems

In order to improve supply chain management and increase competitiveness, it is crucial to integrate supplier selection with other activities at either tactical or operational levels of a supply chain including order allocation (Banaeian, Mobli, Nielsen et al., 2015; V. Jain, Kundu et al., 2015; Memon et al., 2015; Moheb-Alizadeh and Handfield, 2018; Sanayei, Farid Mousavi et al., 2008; Sawik, 2017; Wadhwa and Ravindran, 2007; G. Wang et al., 2005; Weber et al., 2000), inventory management (Firouz et al., 2017; Guo and X. Li, 2014; Sadeque Hamdan and Cheaitou, 2017; Keskin et al., 2010; Mazdeh et al., 2015), vehicle selection (inbound transportation) (Choudhary and R. Shankar, 2013; Choudhary and R. Shankar, 2014; Jafari Songhori et al., 2011; Z. Liao and Rittscher, 2007), production planning (Che, 2010a; Che and H. Wang, 2008; Duan and Ventura, 2019; Paydar and Saidi-Mehrabad, 2017), material flows in a supply chain network design (SCN) (Che, 2010b; Che and H. Wang, 2008; Srinivas Talluri and Baker, 2002; Yeh and Chuang, 2011) and reverse logistics (Amin and Zhang, 2012; Jahangoshai Rezaee et al., 2017; Moghaddam, 2015a; Rezaee et al., 2017; Tsai and Hung, 2009a). Unlike the pure selection problems, which typically focus exclusively on one strategic decision, the focus of integrated selection is to determine strategic, tactical, and operational decisions jointly.

Most of the studies in the integrated selection setting include order allocation, which underlies the implementation of a multi-sourcing strategy, while aiming to determine strategic and tactical decisions in procurement. Regarding said integration, demand can be fittingly split into partial orders to two or more suppliers, without neglecting supplier's capacity (e.g., Mohammaditabar and S. H. Ghodsypour (2016) and Ware et al. (2014)). Therefore, costs incurred due to order allocation are taken into account in joint decision-making, such as unit purchasing and contractual costs (see Moghadam et al. (2008), Ware et al. (2014), and Rezaei and Davoodi (2008)).

Other studies take into account inbound transportation in the suppliers selection process, in order to determine the number of vehicles or carriers. The main objective is reducing inbound transportation costs, since a different vehicle or carrier provided by certain suppliers leads to different unit transportation costs. An appropriate vehicle is also selected while evaluating suppliers, according to either the suppliers' shipping distance (Choudhary and R. Shankar, 2013; Choudhary and R. Shankar, 2014; Z. Liao and Rittscher, 2007) or unit shipping costs (Ghorbani and Ramezanian, 2020), as well as the supplier efficiency score (Jafari Songhori et al., 2011). In those studies, multi-sourcing was taken into account, holding the extension of order allocation. The order allocation was determined through transportation transportation costs under full-truck-load (FTL) (Choudhary and R. Shankar, 2013; Choudhary and R. Shankar, 2014; Jafari Songhori et al., 2011), and less-than-truck-load (LTL) (Z. Liao and Rittscher, 2007).

In addition, several studies incorporate inventory management dealing with decision-making at a strategic (supplier selection), tactical (order allocation), and operational levels (inventory management). Inventory decisions, including order quantity and reorder point (in a single period model)(Firouz et al., 2017; Keskin et al., 2010; Pazhani et al., 2016; Zarindast et al., 2017), or inventory level (in a multi-period model) (Basnet and Leung, 2005; Sadeque Hamdan and Cheaitou, 2017; Mafakheri et al., 2011; Turk et al., 2017), were also determined while performing supplier selection. The objective is to minimize both purchasing and inventory costs. Since the costs associated with a given trip represent a significant part, and any order quantity less than or equal to the load capacity of a vehicle can be charged a flat rate, few studies took into account transportation costs combined with inventory costs (Firouz et al., 2017; Keskin et al., 2010; Pazhani et al., 2016).

A cross-functional activity between procurement and production has been integrated to reduce procurement and production/ shop floor-related costs (Du et al., 2015; Duan and Ventura, 2019; Ling et al., 2006; Nguyen and H. Chen, 2018; Paydar and Saidi-Mehrabad, 2017), as well as to maximize production efficiency (Che, 2017; Che and H. Wang, 2008). Production costs such as material handling, maintenance, and machine overhead costs have been considered important in terms of supplier selection. Decision-making related to production management at tactical (production planning) and operational levels (sequencing and job assignment) have been integrated with supplier selection. Considering production management in the earlier stages of supplier selection can contribute to a competitive advantage since selecting appropriate suppliers can help minimizing the cycle time of assembly lines – consequently increasing the total output (Che and H. Wang, 2008). Besides, it can reduce product delivery time, which, in turn, allows companies to address market demand much faster.

Considering supply chain network design, the supplier selection has been studied involving decisions about plants, distributors, and customers (Che and H. Wang, 2008; Govindan, Mina et al., 2020; Srinivas Talluri and Baker, 2002; Yeh and Chuang, 2011). The decision-making aims to select appropriate suppliers and distributors by taking into account their capacity. Accordingly, the order and shipping quantities to the selected suppliers and distributors respectively, were also determined.

Finally, supplier selection has been addressed to optimize material flows in reverse logistics (e.g., the amount of material in each supply chain party). This problem generally underlies broader horizontal activities across supply chain parties, such as suppliers, plants, disassembly, disposal, and refurbishing sites. This type of decision scope typically aims to maximize profit by taking into account purchasing, production, disassembly, refurbishing, and disposal costs (Amin and Zhang, 2012; Jahangoshai Rezaee et al., 2017; Moghaddam, 2015a; Zouadi et al., 2018).

2.3.3 Decision Environment

The decision environment in supplier selection problems can be classified into two categories: certain and uncertain (as shown in Figure 2.4). We found that most of the studies (54%) focus on uncertain decision environments.

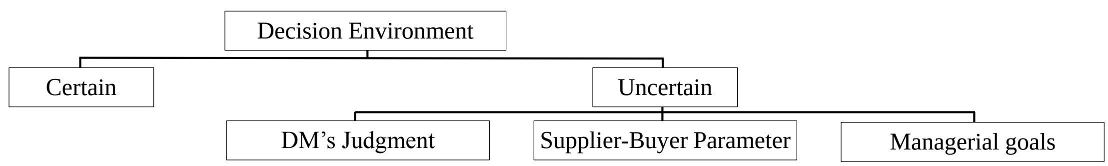


Figure 2.4: Categories of decision environment in supplier selection problems

Supplier selection under a certain decision environment involves deterministic parameters and precise information. By contrast, non-deterministic (stochastic) parameters and vague or imprecise information generally represent the characteristics of an uncertain decision environment. According to these characteristics, we categorize the source of uncertainty in supplier selection problems into decision-makers' judgment, supplier-buyer parameters, and managerial goals (target).

Supplier selection is considered a strategic decision, which typically employs decision-makers or stakeholders' opinion or judgment. In this context, decision-makers' judgment could have an influence in defining and prioritizing supplier selection criteria, as well as assessing suppliers' performance. Uncertainty triggering imprecise judgment in the evaluation of suppliers can occur due to an external factor, such as unquantifiable (intangible), incomplete or insufficient, or non-obtainable information related to suppliers (Amin and Zhang, 2012; Awasthi and G. Kannan, 2016; D. Kannan, Govindan et al., 2015; A. H. Lee, Kang, Hsu et al., 2009).

Moreover, uncertainty can also emerge due to the variability of demand from buyers (Arikan, 2013; Guo and X. Li, 2014; D. Wu and Olson, 2008), as well as unreliability of quality and delivery, decreased supply capacity, and price fluctuation from suppliers (Arikan, 2013; Haleh and Hamidi, 2011; L. Li and Zabinsky, 2011; Moghaddam, 2015a; Mohammed et al., 2018; Razmi and Maghool, 2010; Xu and Yan, 2011). In practice, supply uncertainty usually occurs due to these parameters.

If this uncertainty is not taken into account, selection and purchasing decisions will be sub-optimal (Zarindast et al., 2017).

Since supplier selection typically involves multi-criteria evaluation, managers in charge of purchasing may need to meet important goals that need to be achieved. In terms of supplier selection, minimizing procurement costs, net rejected items, the total rejection rate of a product, the total amount of defective units, the net late delivered items or delivery lateness frequency, and the number of late items are some the most considered goals (Arikan, 2013; Choudhary and R. Shankar, 2014; Memon et al., 2015). In this context, achieving each goal (objective) relies on a target level and specified priority of decision-makers on achieving the target as the goals may not be equally important. In some cases, decision-makers do not have exact and complete information related to objective targets. Hence, it could lead to uncertainty, associated with the subjectivity in human decision-making. Furthermore, supplier selection as a strategic decision might involve a shared interest from different business managers in order to meet enterprise strategy and requirements -particularly considering strategic items (Monczka et al., 2015). The interest can differ among a group of decision-makers due to differences in understanding of requirements, information asymmetry, relevance of objectives, and other subjective reasons (Kar, 2015); these factors could potentially raise uncertainty and prevent decision-makers from reaching a consensus regarding supplier selection.

There are different techniques that can be used to incorporate uncertainty in model parameters. The latter can be represented as fuzzy numbers (e.g., triangular (Arikan, 2013; Haleh and Hamidi, 2011; Moghaddam, 2015a; Razmi and Maghool, 2010), trapezoidal (Xu and Yan, 2011)) and stochastic distributions (e.g., gamma (Razmi and Maghool, 2010), exponential (Amorim et al., 2016)).

2.3.4 Selection Criteria

According to the studies, suppliers are assessed based on multi-criteria, which typically involve qualitative and/or quantitative (as shown in Figure 2.5). Of all reviewed studies, 2% only take into account qualitative criteria, while 52% consider quantitative criteria, and the remaining 46% incorporate both criteria.

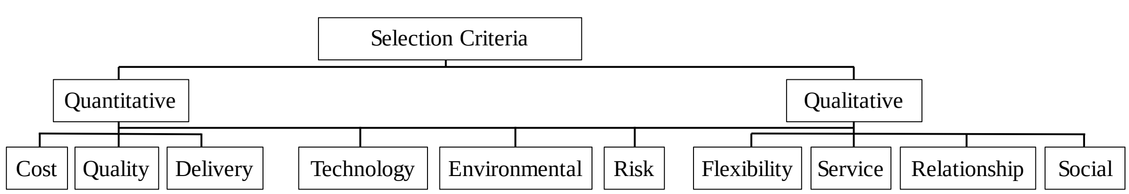


Figure 2.5: Categories of selection criteria (adapted from Hashemi et al. (2015), Parkouhi and Ghadikolaei (2017), Perçin (2006) and Yadav and Sharma (2016))

As key factors in terms of business competitiveness, selection criteria regarding costs, quality, and delivery are strongly taken into account. Typically, these criteria are considered quantitative measures. Concerning the costs criterion, costs components such as unit purchasing, contractual, inventory, fixed, and variable transportation costs have been addressed in the literature. However, only a few studies consider all those aspects (Choudhary and R. Shankar, 2014; Duan and Ventura, 2019; Firouz et al., 2017; D. Kannan, Khodaverdi et al., 2013; Keskin et al., 2010; A. H. Lee, Kang, Lai et al., 2013; Z. Liao and Rittscher, 2007; Rezaei and Davoodi, 2012; Zarindast et al., 2017). A supplier's quality can be assessed according to product specification, number of defects, defect rate, and product reliability. For assessing a supplier's delivery performance, criteria such as delivery time, lead time, order fulfillment rate, on-time delivery, and distance have been considered.

Besides the aforementioned criteria, intangible important criteria that can only be assessed through DM's judgment have also been considered in supplier selection. In this category, qualitative criteria that have been widely used in supplier selection can be classified into technology, services, relationship, and flexibility. Examples of criteria related to technology assessment are the capability of design, innovation, production capability and technological compatibility (D. Kannan, Khodaverdi et al., 2013; Perçin, 2006; Rajesh and Ravi, 2015; Y. Wu et al., 2016). Nevertheless, technology can also be assessed based on tangible criteria, such as productivity, production time, and production capacity (Guarnieri and Trojan, 2019; Yeh and Chuang, 2011). With the evolution of technology, in the context of Industry 4.0, new criteria for supplier selection have been considered, including the level of smart contracts (blockchain), data visibility, traceability (GIS/GPS enabled logistics), and digitalization (cloud computing for resource efficiency and shared platforms) (Z. Chen et al., 2020; Hasan et al., 2020; Kaur and Prakash Singh, 2021). Services from suppliers can be evaluated based on warranty, complaint handling, repair & maintenance services, response to changes, ease of transaction (payment), quality assurance, quality certifications (ISO), and the penalty for delay (Bruno et al., 2012; Demirtas and Üstün, 2008; D. Kannan, Govindan et al., 2015; Kar, 2015; Ustun and Demirtas, 2008; Yadav and Sharma, 2016). Concerning the relationship, criteria including managers' attitude, financial position, mutual trust, honesty, communication, management commitment, information sharing, and geographical location have been used to evaluate suppliers (Abdollahi et al., 2015; Bruno et al., 2012; Hashemi et al., 2015; Kar, 2015; A. H. Lee, Kang, Hsu et al., 2009; Perçin, 2006; Yadav and Sharma, 2016). Criteria such as flexibility in purchase quantity, service, process, and product-mix have been used to evaluate suppliers with respect to the flexibility (Demirtas and Ustun, 2009; Demirtas and Üstün, 2008; D. Kannan, Govindan et al., 2015; Kar, 2015; Parkouhi and Ghadikolaei, 2017; Yadav and Sharma, 2016). We found that these four categories of criteria indicate a buyer's intention in establishing a long-term contract or relationship.

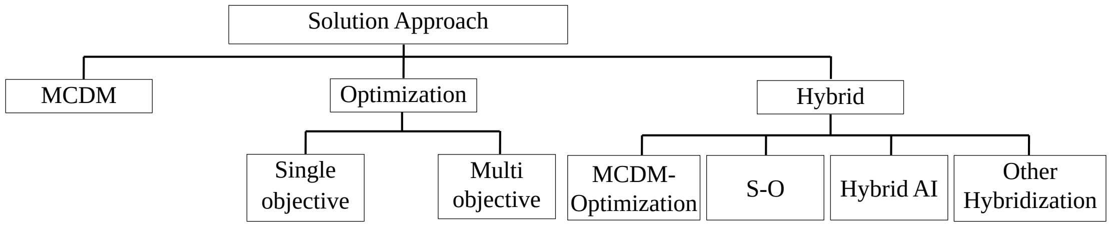
Furthermore, other criteria have been considered to grasp resilience. These criteria are taken into account to mitigate the impact of global supply chains' vulnerability, namely when dealing with unexpected events or disruptions. We classified these criteria in supplier selection as a risk category. In this category, it is worth mentioning risk awareness, vulnerability, disruption management, financial instability, currency volatility, political instability, terrorism, labor strikes, supply capacity instability, and order delays (P.-S. Chen and M.-T. Wu, 2013; Dupont et al., 2018; Kull and S. Talluri, 2008; Parkouhi and Ghadikolaei, 2017; Rajesh and Ravi, 2015; Y. Wu et al., 2016; Yoon et al., 2018).

More recently, sustainability has become a central issue in supplier selection resulting in the adoption of sustainable supply chain initiatives. Green and environmental-related criteria have been addressed in the literature (Awasthi and G. Kannan, 2016; Banaeian, Mobli, Fahimnia et al., 2018; Dobos and Vörösmarty, 2019; Sadeque Hamdan and Cheaitou, 2017; Hashemi et al., 2015; V. Jain, Kumar et al., 2016; Khan-Mohammadi et al., 2018; Mohammed et al., 2018). In this category, criteria such as environmental regulation, sustainability assurance certificate, product recycling, pollution, waste production and treatment, resource consumption, and eco-design have been taken into account in supplier selection. Furthermore, social aspects have also been included as a critical aspect of sustainability (Alikhani et al., 2019; Bai et al., 2019; Z. Chen et al., 2020; Gören, 2018). Criteria including health & safety at work, information disclosure, and the workers' interests and rights are commonly considered.

Sustainability criteria are not easily accessible, certifiable, and audited (Foerstl et al., 2018). In order to avoid this information barrier, distributed ledger technology (such as blockchain) can support the credibility and accessibility of information regarding the whole supply chain across multi-tiers and suppliers (Kouhizadeh and Sarkis, 2018). Although it is still at an early stage, distributed ledger technology shows potential in different issues related to operations management (Babich and Hilary, 2019; Babich and Hilary, 2020; Kouhizadeh and Sarkis, 2018; Saberi et al., 2019). More specifically, in green supplier selection, it facilitates a trustworthy and free-environment between a buyer and supplier through a smart contract, thus reducing opportunistic behaviors between them (Kouhizadeh and Sarkis, 2018; Saberi et al., 2019). The secure and accurate data regarding suppliers' environmental performance made available on blockchain can help companies to improve supplier selection or evaluation processes. This higher perceptibility also applies to the ability to track items through the entire supply chain, or to access information regarding suppliers' capacity at any given time. Z. Chen et al. (2020) and Kaur and Prakash Singh (2021) considered smart technologies as supplier selection criteria for a smart sustainable and resilient supply chain, respectively.

2.3.5 Solution Approach

There are different approaches used to solve supplier selection problems. We classify them into three major categories: multi-criteria decision-making (MCDM), optimization, and hybrid approaches. Figure 2.6 shows the classification of the approaches.



MCDM: Multi-criteria decision making | S-O: Simulation-optimization | AI: Artificial Intelligence

Figure 2.6: Categories of solution approaches for supplier selection

2.3.5.1 MCDM Approach

In general, MCDM approaches are used to tackle pure selection. Typically, a unique optimal solution does not exist in this problem. Therefore, the decision maker's preferences play an important role in differentiating between solutions (Kahraman, 2008). The main selection tasks tackled with this approach involve sorting, ranking, and selection, as well as determining criteria weight (Awasthi and G. Kannan, 2016; Hashemi et al., 2015; A. H. Lee, Kang, Hsu et al., 2009).

In the supplier selection problems, the MCDM approach can be classified into two categories, which are certain and uncertain MCDM. Certain MCDM is applied to deal with complete and precise information. A crisp value represents the value of certain information. Based on the crisp value, an MCDM approach like analytical hierarchy process (AHP) (Matic et al., 2019), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Azimifard et al., 2018), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Abdel-Baset et al., 2019), analytic network process (ANP) (Govindan, M. Shankar et al., 2018; Jiang et al., 2018; Y. Li et al., 2020), Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) (Abdullah et al., 2019; Dulmin and Mininno, 2003), ELimination Et Choice Translating REality (ELECTRE) (Guarnieri and Trojan, 2019) have been employed to tackle supplier selection problems.

Uncertain MCDM relates to decision-makers' ambiguities, uncertainties, and imprecision, which cannot be addressed by using a crisp value. MCDM approaches under uncertainty generally transform a value of information into a fuzzy or interval (grey) number. The use of fuzzy set theory enables decision-makers to incorporate unquantifiable, incomplete and/or non-obtainable information into the decision model, as well as facts that are not fully justified (Kahraman, 2008). The fuzzy set theory has been widely adopted in MCDM approach to solve supplier selection problems including fuzzy AHP (F-AHP) (A. H. Lee, Kang, Hsu et al., 2009; Zimmer, Fröhling, Breun et al., 2017), fuzzy VIKOR (F-VIKOR) (Awasthi, Govindan et al., 2018; Sanayei, Mousavi et al., 2010), fuzzy TOPSIS (F-TOPSIS) (Gupta and Barua, 2018; Rashidi and Cullinane, 2019), fuzzy nominal group technique (F-NGT) (Awasthi and G. Kannan, 2016)), and fuzzy COmbinative Distance-based Assessment (F-CODAS) (Bolturk, 2018). Other MCDM methods have also been proposed to address uncertainty, including Interval-COmplex PRoportional ASsessment (I-COPRA) (Matic et al., 2019), Grey-Simple Additive Weighting technique (G-SAW) (Valipour Parkouhi et al., 2019), and grey TOmada de Decisão Interativa e Multicritério (G-TODIM) (Bai et al., 2019).

2.3.5.2 Optimization Approach

The studies applying optimization approaches usually address an integrated selection problem, including the integration of supplier selection and order allocation (Arikan, 2013; Jadidi, Cavalieri et al., 2015; Kazemi et al., 2015), inventory management (Rezaei and Davoodi, 2008; Rezaei and Davoodi, 2012), transportation (vehicle selection) (Choudhary and R. Shankar, 2014; Z. Liao and Rittscher, 2007; Pazhani et al., 2016), and production planning (Du et al., 2015; Duan and Ventura, 2019; Paydar and Saidi-Mehrabad, 2017). Nevertheless, few studies applied an optimization approach to deal with pure selection (Dobos and Vörösmarty, 2019; Ghoushchi et al., 2020; V. Jain, Kundu et al., 2015; Ng, 2008).

According to the optimization approaches, the supplier selection problem is formulated into a mathematical model and solved according to a different optimization technique. Using these techniques, it is possible to find an optimal or nearly optimal solution. We classify optimization approaches according to the number of objective functions into single-objective and multi-objective.

Single-objective programming with a linear objective function has been proposed to solve supplier selection problems (Amorim et al., 2016; Basnet and Leung, 2005; V. Jain, Kundu et al., 2015; A. H. Lee, Kang, Lai et al., 2013; Ng, 2008; Nguyen and H. Chen, 2018; Rezaei and Davoodi, 2008; Zouadi et al., 2018). Furthermore, several studies applied single-objective programming with a non-linear cost function (S. Ghodsypour and O'Brien, 2001; Guo and X. Li, 2014; Pazhani et al., 2016; Soto et al., 2017; Ware et al., 2014). V. Jain, Kumar et al. (2016) implemented chance-constrained data envelopment analysis (CC-DEA) to select suppliers so that maximum profit can be achieved. Ng (2008) tackled supplier selection based on the suppliers' score by using a transformation technique that enables the weighted linear program to be solved without the need for an optimizer. Rezaei and Davoodi (2008), A. H. Lee, Kang, Lai et al. (2013), Zouadi et al. (2018) and Alfares and Turnadi (2018) solved mixed integer programming (MIP) using a genetic algorithm (GA). A heuristic algorithm, i.e., the Wagner-Within algorithm (W-W algorithm), was used by Basnet and Leung (2005) to solve the MIP model. Nguyen and H. Chen (2018) and Amorim et al. (2016) solved two-phase stochastic programming by using a multi-cut Benders decomposition technique. A supplier selection model with a non-linear constraint (Soto et al., 2017) and objective function (Yang et al., 2011) has been introduced to achieve minimum total costs. To solve this model, GA guided with local search was used to find a near-optimal solution. Instead of using heuristics or metaheuristics, a solver package such as GAMS, CPLEX, GINO, and LINGO have been effectively used to solve mixed-integer non-linear programming (MINLP) (S.

Ghodsypour and O'Brien, 2001; Guo and X. Li, 2014; Pazhani et al., 2016; Ware et al., 2014). Nevertheless, the model solution should not take too long.

A multi-objective setting, with regards to a goal programming variant, has been widely adopted to solve multi-objective programming with a linear function such as preemptive goal programming (PGP), non-preemptive goal programming (non-PGP), weighted fuzzy goal programming (WF-GP) (Choudhary and R. Shankar, 2014), fuzzy relaxed normalized goal programming (F-RNGP) (Jadidi, Zolfaghari et al., 2014), improved multi-choice goal programming (MCGP) (Jadidi, Cavalieri et al., 2015), and interactive fuzzy goal programming (IF-GP) (Kazemi et al., 2015). Furthermore, several studies considered multi-objective (goal) programming with non-linear cost functions. Evolutionary algorithms have been widely applied to solve multi-objective non-linear programming, namely genetic algorithms (GA) (Z. Liao and Rittscher, 2007), nondominated sorting genetic algorithms II (NSGA II) (Rezaei and Davoodi, 2012), and multi-objective genetic algorithms (MOGA) (Yeh and Chuang, 2011).

2.3.5.3 Hybrid Approach

Instead of using a single approach, some studies applied a hybrid approach to address supplier selection. We classify the hybrid approaches into four major categories: MCDM-Optimization, simulation-optimization (S-O), hybrid Artificial Intelligence (hybrid AI), and other hybrids. In accordance with the literature, MCDM-optimization is most widely used to solve supplier selection problems. Similarly to the optimization approach, the studies employing hybrid approaches also address an integrated supplier selection model, which incorporates order allocation (Ayhan and Kilic, 2015; Azadnia et al., 2015; Banaeian, Mobli, Nielsen et al., 2015; Che and H. Wang, 2008; S. Hamdan and Jarndal, 2017; Sadeque Hamdan and Cheaitou, 2017; Kokangul and Susuz, 2009; Narasimhan et al., 2006; Perçin, 2006; Scott et al., 2015; R.-C. Wang and Liang, 2004; Xia and Z. Wu, 2007), inventory management (Firouz et al., 2017; Hasan et al., 2020; Hlioui et al., 2017; Jolai et al., 2011; Keskin et al., 2010; Mafakheri et al., 2011; Razmi and Rafiei, 2010; Ustun and Demirtas, 2008), vehicle selection (Jafari Songhori et al., 2011) and material flows in the reverse logistics or closed-loop supply chain (Amin and Zhang, 2012; Moghaddam, 2015a; Moghaddam, 2015b). Moreover, hybrid approaches have also been applied to pure selection problems (Abdollahi et al., 2015; P.-S. Chen and M.-T. Wu, 2013; Igoulalene et al., 2015; Kar, 2014; Kar, 2015; Karsak and Dursun, 2014; Kellner et al., 2019).

MCDM-Optimization

An MCDM-Optimization approach incorporating qualitative and quantitative criteria relies on two-phase decision-making. Basically, MCDM is employed to determine the value of purchasing representing a score of supplier performance, which involves qualitative and quantitative criteria. The optimization considers a different approach and it is undertaken in the second phase of the process.

Mathematical programming has been widely combined with MCDM, including data envelopment analysis and multi-objective mixed-integer linear programming (DEA-MOMILP) (Jafari Songhori et al., 2011), ANP-MOMILP (Razmi and Rafiei, 2010; Ustun and Demirtas, 2008), AHP-MOMILP (Kokangul and Susuz, 2009; Mafakheri et al., 2011; Narasimhan et al., 2006; Xia and Z. Wu, 2007), TOPSIS-MOMILP (D. Kannan, Khodaverdi et al., 2013; Mohammed et al., 2018), multi-attribute utility theory and linear programming (MAUT-LP) (Sanayei, Farid Mousavi et al., 2008), TOPSIS-LP (Kilic, 2013; L. Li and Zabinsky, 2011; A. Singh, 2014), AHP-GP (Che and H. Wang, 2008; Perçin, 2006; R.-C. Wang and Liang, 2004), AHP-MCGP (C.-N. Liao and Kao, 2011), TOPSIS-GP (Hasan et al., 2020; Jolai et al., 2011), TOPSIS-MCGP (Hasan et al., 2020), and best-worst method and MCGP (BWM-MCGP) (Cheraghalipour and Farsad, 2018).

Furthermore, metaheuristics, such as particle swarm optimization (PSO) and GA have also been hybridized with MCDM methods in the literature. Some of them include AHP-PSO (Che, 2010a) and AHP-GA (S. Hamdan and Jarndal, 2017; Sadeque Hamdan and Cheaitou, 2017).

Simulation-Optimization

Based on the simulation purpose within this hybridization suggested by Figueira and Almada-Lobo (2014), simulation-optimization can be divided into evaluation function (EF), surrogate model construction (SMC), analytical model enhancement (AME), and solution generation (SG). In supplier selection, simulation-optimization is usually developed using EF. Keskin et al. (2010) and Firouz et al. (2017) proposed hybrid scatter search and simulation. Supplier selection decisions were optimized by scatter search, considering the costs obtained from the simulation. Hlioui et al. (2017) applied a hybrid simulation and response surface methodology. The simulation was used for the construction of a surrogate model (SMC). The Response Surface Methodology was used to determine the relationship between supplier and inventory decisions, which become the simulation inputs, interactions, and the total cost. Moghaddam (2015b) proposed a hybrid Monte Carlo simulation and goal programming, generating goals for each objective function and weights of the goals' deviations.

Hybrid Artificial Intelligence

One can use this approach to address pure and integrated selection problems. Artificial Intelligence tools and approaches, including: *(i) fuzzy set theory*, used to address the imprecision and uncertainty inherent to human judgment in decision making processes (i.e., fuzzy consensus-based neat OWA and goal programming (Igoulalene et al., 2015); interval and hesitant fuzzy technique (IHF) (Chai and Ngai, 2015); interval-valued intuitionistic uncertain linguistic (IVIUL) (H.-C. Liu et al., 2019); fuzzy group graph theory and matrix approach (FGGTMA) (KhanMohammadi et al., 2018); fuzzy axiomatic design (F-AD) (D. Kannan, Govindan et al., 2015), and fuzzy Kano model-based FIS (fuzzy interface system) (N. Jain and A. R. Singh, 2020)); *(ii) grey system theory*, which is applied to imprecise information in the form of interval values (i.e., GRA (grey relational analysis) (Rajesh and Ravi, 2015); F-GRA (Haeri and Rezaei, 2019); F-GRA and MILP (Banaeian, Mobli, Nielsen et al., 2015); GRA and chance-constrained goal programming (CCGP) (Memon et al., 2015)); *(iii) expert systems*, applied to incorporate the experts' opinion and knowledge in the field through a series of IF-THEN rules (i.e., hybrid knowledge base and bi-objective mathematical programming (Ghadimi et al., 2018)), *(iv) Bayesian network*, which uses probabilistic graphical models to represent uncertainty (i.e., DEMATEL-Bayesian Network (Kaya and Yet, 2019)), *(v) Dempster–Shafer theory (DST)*, which is used to combine unexpected empirical evidence regarding the evaluation of judgement and consequently organize a coherent picture of reality (i.e., Dempster–Shafer VIKOR (DS-VIKOR) (Liguo Fei et al., 2019); Dempster–Shafer ELECTRE (DS-ELECTRE) (L. Fei et al., 2019)); and *(vi) neural network (NN)*, which helps the network predicting the correct class label for the input objects based on the weight associated to the connection of an input-output in the learning phase (i.e., F-AHP and Fuzzy Neural Network (F-NN) (Kar, 2015)), have been extended to solve supplier selection.

Other Hybridizations

Some studies in the literature applied a hybrid approach, which is not included in the three main categories discussed before, such as quality function deployment (QFD), statistical models, failure mode and effect analysis (FMEA), strengths-weakness-opportunities-threats analysis (SWOT), and game theory. In this classification, the majority of the studies applied QFD and statistical models for supplier selection.

For studies employing QFD for supplier selection, inner dependence among supplier evaluation criteria is assessed by creating a house of quality (HOQ). This method has been combined with DEA (Karsak and Dursun, 2014), MOMILP Bevilacqua et al. (2006), AHP and chance-constrained programming (CCP) (Scott et al., 2015).

The hybrid statistical models, such as fuzzy six sigma and the statistical analysis proposed by K.-S. Chen et al. (2019), were used for supplier selection concerning the quality of final products. Another statistical model proposed by Davoudabadi et al. (2020), namely principal component analysis (PCA), has been integrated with DEA to reduce the dimensions and the correlation between the criteria in supplier selection. Srinivas Talluri and Narasimhan (2003) used hybrid DEA and Kruskall-Wallis test for suppliers clusterization.

The remaining approaches are found to be less explored. Jahangoshai Rezaee et al. (2017) applied an integrated DEA and Nash bargaining game to create a competitive environment between suppliers, namely when the buyer defines a minimum efficiency level. Amin, Razmi et al. (2011) proposed a hybrid approach using fuzzy SWOT and fuzzy LP enabling decision-makers to evaluate suppliers under imprecise judgment and to identify suppliers' portfolios based on internal and external factors. Finally, P.-S. Chen and M.-T. Wu (2013) presented a study of supplier selection in the supply chain risk environment using hybrid AHP and modified failure mode effect analysis (M-FMEA).

2.4 Supplier Selection Framework

2.4.1 Formulating Supplier Selection Problems for Different Types of Items and Production Policies

The problem statement in supplier selection needs to be appropriately addressed, which includes determining the sourcing strategy, the incorporation of related supply chain activities (decision scope), and uncertainty (decision environment), while identifying supplier selection criteria. Due to the different characteristics of items and industrial settings, namely in terms of the production policy, supplier selection needs to be formulated accordingly. From the reviewed studies, we extract the appropriate problem setting for each combination of production policy and type of item, which is summarized in Table 2.1.

Concerning the types of items, we found that the reviewed studies focus on the supplier selection for strategic, bottleneck, and leverage items. None of the studies deal with non-critical items due to their low complexity and importance. Their acquisition process should be simplified, and the final selection for its supplier should be more straightforward. Direct purchase or day-to-day purchases can be performed through an online vendor catalog to reduce time and effort (Monczka et al., 2015).

In supplier selection problems, the sourcing strategy varies depending on the complexity of supply and other factors associated with the production policy. Sourcing strategy for strategic and bottleneck items typically follows multi-sourcing with a single period model for all production policies (Amin, Razmi et al., 2011; Ayhan and Kilic, 2015; V. Jain, Kundu et al., 2015; Kokangul and Susuz, 2009; Kull and S. Talluri, 2008; Scott et al., 2015). Multi-sourcing can be applied to mitigate the high risks of supply, particularly for strategic and bottleneck items. For instance, a disruptive event can trigger a significant loss to buyers due to the unreliability of suppliers to perform their operation or even due to their absence. A multi-sourcing strategy enables buyers to split and rely on to other suppliers, who can then compensate the disruptions of the former. A single-period model in ATO and MTS typically indicates a medium-to-long-term demand plan. It also implies the intention to develop good supplier relationships in order to ease the communication, consolidation, and coordination, as well as to maintain the continuity of supply and mitigate the risk of supply. Meanwhile, the application of a single-period in ETO and MTO holds a different principle depending on the customization, the so-called versatile manufacturing company (VMC) (see Stevenson et al. (2005) for more detail). In VMC, where the purchase volume is low, and the customization is high, the demand fulfillment is typically based on a single-period under short-term planning. A long-term supplier relationship is not necessary in these cases. Contrary to the strategic and bottleneck items, leverage items apply single-sourcing due to low risk of supply (Soto et al., 2017). Nevertheless, multi-sourcing may also be applied since this type of items constitutes high volume demand while suppliers' capacity is limited in practice (Azadnia et al., 2015; Kilic and Yalcin, 2020). For leverage items, with a high number of suppliers and source availability, buyers may focus on selecting suppliers based on a multi-period under a short-term contract (Azadnia et al., 2015; Babbar and Amin, 2018; Mohammed et al., 2018; Soto et al., 2017). However, since this type of items substantially impacts profit, buyers can also consider selecting suppliers under a medium-term contract to maintain a high level of quality and reduce the total costs to the business.

Table 2.1: Sourcing strategy, criteria, decision scope and decision environment based on the KPM and production policy

Production Policy	Types of item	Dimensions				
		Sourcing	**Period**	**Criteria**	**Scope**	**Decision Environment**
ETO	**Strategic, Bottleneck**	Multi	Single	**Winner:** technology capability (Ql)(technical capability, product innovation capability, technological compatibility); lead time (Qn) (design, manufacturing & delivery); Quantity flexibility (Qn); risk factor (Qn); **Qualifier:** purchasing cost (Qn)	OA	Supplier-buyer parameters, DMs' judgment
	Leverage	Single	Single	**Winner:** purchasing cost; **Qualifier:** : technology capability (Ql)(technical capability, product innovation capability, technological compatibility); lead time (Qn) (design, manufacturing & delivery); Quantity flexibility (Qn)	PS	Supplier-buyer parameters
MTO	**Strategic, Bottleneck**	Multi	Single	**Winner:** technology capability (Ql)(technical capability, product innovation capability, technological compatibility); lead time (Qn) (design, manufacturing & delivery); Quantity flexibility (Qn); risk factor (Qn); **Qualifier:** purchasing cost (Qn)	OA, PP	DMs' judgment; Supplier-buyer parameters
	Leverage	Single	Single	**Winner:** purchasing cost (Qn); transportation cost (Qn); **Qualifier:** technology capability (Ql)(technical capability, product innovation capability, technological compatibility); lead time (Qn) (design, manufacturing & delivery); Quantity flexibility (Qn)	PS	Supplier-buyer parameters
ATO/MTS	**Strategic**	Multi	Single	**Winner:** contractual cost (Qn); purchasing cost; inventory cost (Qn); transportation cost (Qn); supply capacity (Qn); relationship (Ql)(management commitment, honesty, reputation, communication); risk factor (Qn)	OA, PP, I	Supplier-buyer parameters; DMs' judgment; Managerial goals
	Bottleneck	Multi	Single	**Winner:** supply capacity (Qn); relationship (Ql)(management commitment, honesty, reputation, communication); risk factor (Qn) **Qualifier:** contractual cost (Qn); purchasing cost; inventory cost (Qn); transportation cost (Qn)	OA, PP, I	Supplier-buyer parameters; DMs' judgment; Managerial goals
	Leverage	Single	Multi	**Winner:** purchasing cost; inventory cost; transportation cost; **Qualifier:** supply capacity (Qn)	PS, I	Supplier-buyer parameters

Ql: Qualitative criteria | Qn: Quantitative criteria | OA: Order allocation | PS: Pure selection | I: Inventory management | PP: Production planning

The appropriateness of supplier selection criteria depends on purchasing's importance and the issues that raise the production policy's challenges. For instance, ETO and MTO production policies in which the purchasing and production activities are only done after receiving customer orders and products are manufactured to meet specific customers needs, requires reliability in manufacturing lead time and product requirements. Therefore, incorporating these concerns into supplier selection criteria is essential to the implementation of the production policy. Supplier selection criteria, including suppliers' product design, innovation, production capabilities, and technological compatibility, are taken into account as means to meet customer's requirements in ETO and MTO production policies (Dulmin and Mininno, 2003; D. Kannan, Khodaverdi et al., 2013; Perçin, 2006; Rajesh and Ravi, 2015; Y. Wu et al., 2016; Yousefi et al., 2017). In addition, suppliers' production (design) and delivery time are also considered critical criteria in supplier selection for ETO and MTO (Awasthi and G. Kannan, 2016; Dulmin and Mininno, 2003; V. Jain, Kundu et al., 2015; Rajesh and Ravi, 2015). Criterion such as flexibility of purchase quantity is also essential to consider (Z. Chen et al., 2020; Xu and Ding, 2011), since the demand volume in these production policies is unique for each customer orders. In MTS and ATO, where a customer's order is met from stock, inventory management becomes the main issue. Criteria such as inventory cost are taken into account in this case (Ayhan and Kilic, 2015; A. H. Lee, Kang, Lai et al., 2013; Soto et al., 2017; Yin et al., 2015).

Furthermore, the order winners and qualifiers related to the supplier selection vary depending on the importance of purchasing. For the items that have a high impact on profit, such as strategic and leverage, the criteria should be focused on the monetary base orientation to reduce total cost. For leverage items, order winners can be determined based on monetary criteria (V. Jain, Kundu et al., 2015; A. H. Lee, Kang, Lai et al., 2013; Moghadam et al., 2008; Soto et al., 2017), since the number of suppliers and substitution possibilities are large. Therefore, a buyer has more power in a negotiation, and a monopoly on the pricing does not exist among suppliers. For strategic items, due to a high volume of purchases (except in ETO and MTO), a buyer can approach suppliers to negotiate pricing options for specific purchase volumes. This negotiation enables a buyer to reduce costs through different pricing strategies (V. Jain, Kundu et al., 2015). However, it requires an effort to pursue negotiations with suppliers since the number of suppliers is small. In addition, suppliers are usually in control in said negotiations, and very little competition exists among them. Buyers also need to maintain a high quality since these types of items are important to the business. Competitive bidding can be very useful in maintaining a reduced price and a high level of quality (Gelderman and Weele, 2003).

With the increase of the items' importance on the operations, such as strategic items, non-monetary based oriented criteria (i.e., technology, relationship, flexibility) are also important (Azadnia et al., 2015; Demirtas and Ustun, 2009; Kokangul and Susuz, 2009; Ustun and Demirtas, 2008). Bottleneck items indicate a low impact on profits but a high impact on operations. The main focus of managing this type of items is to ensure continuity of supply. Criteria for selecting bottleneck items' suppliers can be more focused on achieving a non-monetary added-value (Amin, Razmi et al., 2011; Che, 2017; Lin et al., 2011; R.-C. Wang and Liang, 2004). Reducing total costs for bottleneck items is not easily achieved because buyers encounter high switching costs and lack negotiating power due to small purchase volume. Besides, suppliers have more power due to their ability to provide inputs that are important to the operation. However, buyers might make an effort to negotiate with suppliers through competitive bidding to obtain a lower purchasing price.

The supply complexity also brings specific supplier selection criteria. Considering long-term relationships in terms of supplier selection is considered beneficial to reduce the impact of risk factors triggering supply complexity. Concerning this kind of relationship, criteria such as management commitment, honesty, reputation, communication, and disruption management have been taken into account in the selection of bottleneck and strategic items, particularly in ATO and MTS (Amin, Razmi et al., 2011; Hashemi et al., 2015; Lin et al., 2011).

The factors, including supply complexity (i.e., the implementation of sourcing strategy), importance of purchasing (i.e., the incorporation of the criteria), and production policy play a role in the integration of activities in supplier selection. For instance, the decision scope becomes larger by including order allocation, when implementing a multi-sourcing strategy for bottleneck and strategic items (Kilic, 2013; Scott et al., 2015; Xu and Ding, 2011). In addition, the decision scope remains large, even for leverage items, whenever the pivotal criteria affecting the success of a production policy implementation are incorporated. Regarding the decision scope, inventory management are often integrated with supplier selection, particularly in ATO and MTS (A. H. Lee, Kang, Lai et al., 2013; Soto et al., 2017). Exceptionally, in ETO, the decision scope for leverage items only deals with pure selection due to the characteristics of its customization (Dulmin and Mininno, 2003; Y. Wu et al., 2016).

The source of uncertainty in supplier selection problems becomes more diverse with the increase of supply and production complexities, as well as with the increase of purchasing importance. For instance, the source of uncertainty, including supplier-buyer parameters and decision maker's judgment, exist for strategic and bottleneck items due to high supply complexity (Amin, Razmi et al., 2011; Du et al., 2015; Scott et al., 2015). The diversity of the source of uncertainty related to the supplier-buyer parameters also varies. For example, demand is typically known and certain in ETO and MTO. However, other parameters related to suppliers such as quality, lead time, and price are often uncertain due to the supply complexity (Awasthi, Govindan et al., 2018; Y. Wu et al., 2016; Zimmer, Fröhling, Breun et al., 2017). For the items that have a significant impact on profit and operations, such as strategic items, setting up precise managerial targets (goals) appears to be difficult since it requires careful consideration within enterprise strategy and requirements. Typically, in ATO and MTS, to relax the preferences, decision-makers usually define their targets or goals as imprecise values (D. Kannan, Khodaverdi et al., 2013; Tsai and Hung, 2009b). In ETO and MTO, managerial targets are known precisely (Kull and S. Talluri, 2008;

A. H. Lee, Kang, Hsu et al., 2009; Perçin, 2006), since the product or purchase requirements are typically specified by customers.

2.4.2 Approaching Different Supplier Selection Problems

Once the problem statement is determined appropriately, a suitable solution approach is demanded to solve it. As not all the approaches are equally useful in every possible purchasing situation (de'Boer et al., 2001), we seek to analyze the suitability of the approaches in dealing with the dimensions according to the problem statements discussed earlier. Table 2.2 shows the suitability of the approaches to address said different problems.

Based on the analysis, one can observe hybrid approaches prevail both in tackling a broader scope of supplier selection problems, as well as in incorporating criteria holistically and uncertainty. MCDM-Optimization is noticeably the most widely used hybridization. Indeed, this combination has several benefits. First, both qualitative (flexibility, service, environment management, green image) and quantitative criteria (quality, price, order fulfill rate) can be well incorporated in the supplier selection (Azadnia et al., 2015; Demirtas and Ustun, 2009; Kull and S. Talluri, 2008; Perçin, 2006; A. Singh, 2014; Ustun and Demirtas, 2008). This would be difficult using standalone mathematical optimization models. Second, multiple phases, such as criteria weighting, supplier evaluation (performance assessment), and constraint assurance, can be used to accommodate decision-makers' preferences while seeking the optimal solution (Azadnia et al., 2015; Demirtas and Ustun, 2009; Kull and S. Talluri, 2008; Perçin, 2006; A. Singh, 2014; Ustun and Demirtas, 2008). Third, interrelated decisions (e.g., order allocation, vehicle selection, and inventory replenishment), which may involve a large number of alternatives, can be properly evaluated. Therefore, steps such as pre-qualification, may not necessarily be performed as they can be jointly optimized. MCDM-Optimization appears to be applicable for solving supplier selection problems that fit almost all the characteristics of the dimensions. For instance, it can accommodate various types of sources of uncertainty, including supplier-buyer parameters (Govindan, Mina et al., 2020; Haleh and Hamidi, 2011), DMs' judgment (Ayhan and Kilic, 2015; Azadnia et al., 2015; Che, 2010b; Kilic, 2013), and managerial target (D. Kannan, Khodaverdi et al., 2013; Mohammed et al., 2018; Tsai and Hung, 2009b).

However, not all the hybrid approaches are equally useful and applicable in dealing with the different criteria, decision scopes, and environments. S-O is more suitable to incorporate quantitative criteria and is very useful for tackling integrated problems and representing some particular sources of uncertainty, such as supplier-buyer parameter (Firouz et al., 2017; Hlioui et al., 2017; Keskin et al., 2010) and managerial targets or goals (Moghaddam, 2015a). Hybrid AI is limited to the incorporation of uncertainty into decision-makers' judgment (Kar, 2015; Kaya and Yet, 2019). However, the applicability of this approach to the decision scope is large, including pure and integrated selection (Ghadimi et al., 2018).

Single-based approaches are useful for specific problem statements dealing with either criteria, decision scope, or decision environment. For the type of items and production policy that follow the pure selection, the problems generally incorporate supplier selection criteria, including both qualitative and qualitative criteria. In these cases, a pure MCDM is sufficient to accommodate the criteria and obtain a solution that satisfies the decision maker's preferences (Azimifard et al., 2018; Dulmin and Mininno, 2003; Yadav and Sharma, 2016). In addition, MCDM can also be applied to incorporate uncertainty, mainly dealing with DMs' judgment (Banaeian, Mobli, Fahimnia et al., 2018; A. H. Lee, Kang, Hsu et al., 2009; Zimmer, Fröhling, Breun et al., 2017). However, MCDM can appropriately perform when the number of alternatives is relatively small due to the consistency assurance in supplier evaluation (Saputro et al., 2015). This indicates that it is necessary to perform pre-qualification to reduce the number of possible alternatives when solely employing MCDM. Thus, the inconsistency of human judgment can be avoided. On the other hand, pure selection can also be effectively tackled using pure optimization, considering that all selection criteria are measurable (quantitative). Furthermore, optimization is useful in tackling a complex problem and incorporating decisions (i.e. strategic and tactical), that are solved simultaneously, such as order allocation, inventory management, and production planning.

All the approaches (hybrids and optimization) are useful to address single and multi-sourcing strategies, as well as single and multi-period (Firouz et al., 2017; Ghadimi et al., 2018; Keskin et al., 2010; A. H. Lee, Kang, Lai et al., 2013; Scott et al., 2015; Soto et al., 2017; Yeh and Chuang, 2011). Exceptionally, MCDM is useful when only the problems hold single-sourcing with a single period (Azimifard et al., 2018; Banaeian, Mobli, Fahimnia et al., 2018; Dulmin and Mininno, 2003; A. H. Lee, Kang, Hsu et al., 2009; Yadav and Sharma, 2016; Zimmer, Fröhling, Breun et al., 2017).

According to the analysis, we found that among the dimensions, supplier selection criteria, decision scope, and decision environment play a vital role in the applicability and suitability of the approaches. Additionally, the extent of the decision scope relies on the implementation of a multi-sourcing strategy and the incorporation of supplier selection criteria, which typically depend on the purchasing importance and production policy. To tackle supplier selection of items whose supply complexity is high (i.e., strategic and bottleneck items), hybrid approaches can be used. For items with a low supply complexity (as the decision scope and environments' driver) (i.e., leverage items), stand alone approaches, including optimization and MCDM can be employed to solve the problems. To incorporate both qualitative and quantitative criteria (i.e., for strategic items), MCDM-optimization and Hybrid AI are the appropriate approaches.

Table 2.2: Approaches for the different supplier selection problems

Criteria	**Decision Environment**		**Scope**	
			Pure Selection	**Integrated Selection**
			Single sourcing-Single period	**All sourcing strategies**
Qualitative	**Certain**		MCDM, MCDM-Optimization, Hybrid AI	MCDM-Optimization
	Uncertain	**DM's judgement**		
		Supplier-Buyer parameter	N/A	
		Managerial target (goals)	MCDM-Optimization, Hybrid AI	
Quantitative	**Certain**		Optimization, MCDM-Optimization, Hybrid AI	Optimization, MCDM-Optimization
	Uncertain	**DM's judgement**	MCDM-Optimization, Hybrid AI	MCDM-Optimization
		Supplier-Buyer parameter	Optimization, S-O	Optimization, S-O, MCDM-Optimization
		Managerial target (goals)	Optimization, MCDM-Optimization, Hybrid AI	

2.5 Trends and Opportunities for Future Work

This paper provides a theoretical framework that is useful to deal with the supplier selection process, particularly in determining the critical dimensions so that the problem can be appropriately formulated and solved. Holding the principle of Kraljic's purchasing classification, as well as incorporating the concept of production policy, the framework is proposed to fit the different types of items comprising different importance levels of purchasing, and different production and supply complexities. Over 150 published papers focusing on supplier selection are then discussed in light of the novel framework.

Our review highlights the recent developments on the supplier selection studies (e.g., source of uncertainty in supplier selection, sourcing strategy and critical criteria in the current challenge, extensive selection criteria in supply chain network design) and improves the range of works reported by the previous reviews (e.g., the widespread approaches reported by Aissaoui et al. (2007), Chai and Ngai (2015), Ho et al. (2010), Ocampo et al. (2018) and Simić et al. (2017)). Four major research trends emerge from our review.

- **Fostering supply chain resilience through risks mitigation** - In today's global market, which is quite challenging, the decision environment in supplier selection is found to be highly uncertain. The source of uncertainty coming from buyers (i.e., demand) and suppliers (quality, capacity, price, lead time) could contribute to a failure to meet customer demand without a proper sourcing strategy (Haleh and Hamidi, 2011) and supplier selection (L. Li and Zabinsky, 2011). Our review shows that multi-sourcing is the most common strategy considered in supplier selection. This strategy is considered appropriate to approach the supply of items whose supply risks are high (i.e., strategic and bottleneck items), particularly when suppliers experience capacity issues and suffer from disruptions (Firouz et al., 2017). More extensively, recent studies have taken into account resilient supplier selection criteria focusing on risk mitigation for these types of items. Risk-related quality and delivery were found to be the most common factors studied in supplier selection. Solution approaches have been developed, particularly for assessing risk factors. MCDM approaches were often used to evaluate suppliers' risk profiles. Other sources of uncertainty, including decision maker's judgment and managerial goals (target), enhance supplier selection complexity. According to our review, the uncertainty of the decision maker's judgment has been intensively addressed, mainly in terms of the pure selection. To incorporate these uncertainties (managerial goals and DMs' judgment), fuzzy set theory has been widely applied.
- **Embracing sustainability goals** - More recently, supplier selection criteria have evolved rapidly, from green to sustainable concepts, considering economic, social, and environmental criteria (Bai et al., 2019; Z. Chen et al., 2020; Gören, 2018). In the closed-loop supply chain or reverse logistics, mainly in the high-

tech industry (i.e., automotive, electronic, and energy industries), sustainability is essential to improve the design of the supply chain network (Govindan, Mina et al., 2020). This integrated selection is generally concerned with strategic and tactical decisions, in a wide scope involving multiple objectives. Since the right supplier selection approaches depend on the criteria and the decision scope (which relies on the sourcing strategy and criteria), MCDM-optimization is widely used to solve this problem, thus dealing with the aforementioned dimensions.

- **Integrating supply chain processes** - Our review shows that the more complex the supply and the more important the purchasing process are, the wider the decision scope and the more diverse the source of uncertainty are. Integrating supplier selection with supply chain activities, including order allocation, inventory management, and production planning, is essential in this context (Duan and Ventura, 2019; Sadeque Hamdan and Cheaitou, 2017). In addition, there is an increased added value to achieve, and additional criteria to consider. The suitability of the approach in supplier selection appears to be dependent on both the complexity of supply and production, as well as on the importance of purchasing. In other words, a particular situation related to sourcing strategy, supplier selection criteria, decision environment, and decision scope should be addressed through a specific approach, such as hybrid approaches (MCDM-Optimization, Simulation-Optimization, Hybrid AI) for the complex problems.

- **Considering distributed ledger technology adoption** - Establishing mutually beneficial long-term supplier relationships, particularly for strategic items, is a vital step in enhancing a firm's performance across the supply chain. The adoption of distributed ledger technology (i.e., blockchain) can improve the supplier selection process (Z. Chen et al., 2020; Kaur and Prakash Singh, 2021), thus enabling a firm and suppliers to build mutual trust and honesty through trace-ability and transparency of the shared information using smart contracts (Babich and Hilary, 2020). Furthermore, the suppliers' historical performance and data that are not easily accessible or certifiable, especially in sustainability and resilience criteria underlying the research trends, can be accommodated effectively using blockchain technology. Therefore, in the presence of this technology, suppliers' participation in a blockchain system plays a key role, with its associated selection criteria supporting this initiative (i.e., management commitment, sharing information, ease of communication (Hashemi et al., 2015; Lin et al., 2011; A. Singh, 2014; Yadav and Sharma, 2016), and technology capability (Z. Chen et al., 2020; Hasan et al., 2020; Kaur and Prakash Singh, 2021)).

Table 2.3: Research opportunities in supplier selection problems

SCOPE	DECISION ENVIRONMENT	Single Sourcing				Multi Sourcing			
		Single Item		Multi Item		Single Item		Multi Item	
		Single Period	Multi Period	Single Period	Multi Period	Single Period	Multi Period	Single Period	Multi Period
Pure	Certain	Chen & Wu (2013); Jain et al. (2016); Azimifard et al. (2018); Govindan et al. (2018); Kaya & Yet (2019); Matic et al. (2019); Gao et al. (2020)	Not Applicable						
	Uncertain	Abdollahi et al. (2015); Chai & Ngai (2015); Awasthi & Kannan (2016); Wu et al. (2016); Zimmer et al. (2017); KhanMohammadi et al. (2018); Chen at al. (2019); Lu et al. (2019); Singh (2020); Chen et al. (2020)							
Order Allocation	Certain	Not Applicable				Weber et al. (2000); Sanayei, Farid Mousavi, Abdi, and Mohaghar (2008); Kokangul and Susuz (2009); Demirtas and Üstün (2008); Kull and Talluri (2008); Liao & Kao (2010); Lin et al. (2011); Talluri and Narasimhan (2003); Jadidi et al. (2015);	Talluri et al. (2018)	Wadhwa and Ravindran (2007); Wang et al. (2004); Wang et al. (2005); Perçin (2006); Xia and Wu (2007); Yousefi et a. (2017); Narasimhan et al. (2006); Ghadimi et al. (2018)	Ware, Singh, and Banwet (2014); Moheb-Alizadeh & Handfield (2019)
	Uncertain					Memon, Lee, and Mari (2015); Scott et al. (2015); Wu and Olson (2008b); Xu and Ding (2011); Sawik (2011); Arikan (2013); Kazemi et. al (2015); Jadidi, Zolfaghari, and Cavalieri (2014); Banaeian et al. (2015); Kannan, Khodaverdi, Olfat, Jafarian, and Diabat (2013); Singh (2014); Mohammed et al. (2018)		Li and Zabinsky (2011); Ayhan and Kilic (2015); Amin et al. (2011); Ozkok and Tiryaki (2011); Xu and Yan (2011), Kilic (2013)	Babbar & Amin (2018); Cheraghalipour et al. (2018); Razmi and Maghool (2010); Haleh and Hamidi (2011); Goren (2018); Kilic & Yalcin (2020); Kaur & Singh (2020)
Vehicle Selection	Certain					Liao and Rittscher (2007)	Jafari Songhori et al. (2011); Choudhary and Shankar (2013);		
	Uncertain			(i)		Ghorbani & Ramezanian (2020)	Choudhary and Shankar (2014)	(i)	
Inventory Mangement	Certain		Mazdeh, Emadikhiav, and Parsa (2015); Soto et al. (2017)			Mendoza and Ventura (2008); Pazhani et al. (2016); Ghodsypour and O'Brien (2001)	Mafakheri, Breton, and Ghoniem (2011); Ustun and Demiʼrtas (2008); Lee, Kang, Lai, and Hong (2013); Demirtas and Üstün (2009); Hamdan & Jarndal (2017); Razmi and Rafiei (2010)	Mohammaditabar and Ghodsypour (2016);	Basnet and Leung (2005); Rezaei and Davoodi (2012); Moghadam et al. (2008); Rezaei and Davoodi (2008); Alfares et al. (2019)
	Uncertain	Keskin, Melouk, and Meyer (2010)	(ii)	Hlioui et al. (2017); Yang et al. (2011)	(ii)	Guo and Li (2014), Keskin, Melouk, and Firouz (2017); Jain, Kundu, Chan, and Patel (2015)	Zarindast et al. (2017); Cheaitou & Hamdan (2017)	(ii)	Turk et al. (2017); Azadnia et al. (2015); Jolai et al. (2012)
Production Planning	Certain			Che (2017)		Ling et al. (2006)	Duan & Ventura (2018)		Paydar & Mehrabad (2017); Che (2010a)
	Uncertain		Nguyen & Chen (2018)		(iii)			Du et al. (2015)	Yin, Nishi, and Grossmann (2015);
Reverse Logistics (Closed-Loop Supply Chain)	Certain	Talluri and Baker (2002)				Yeh and Chuang (2011);	Zouadi et al. (2018)	Rezaee et al. (2017)	
	Uncertain		(iv)	Govindan et al. (2020)	(iv)	Che (2010b)		Moghaddam (2015a); Moghaddam (2015b); Amin and Zhang (2012); Tsai et al. (2009)	Amorim et al. (2016)

Explored Implicitly Explored Unexplored

Although uncertainty has been widely considered in the literature, the vast majority of research does not incorporate uncertain parameters, particularly from suppliers, such as their capacity, quality, and delivery (Arikan, 2013; Guo and X. Li, 2014; Moghadam et al., 2008; D. Wu and Olson, 2008; Yin et al., 2015). In addition, criteria used for supplier selection need to be revised, especially in the context of distributed ledger technology and sustainability goals. Moreover, most studies address the problem by considering just a few of the relevant dimensions, therefore leading to significant gaps. Table 2.3 summarizes supplier selection problems from past studies according to critical dimensions, including sourcing strategy, decision environment, and decision scope. For instance, the integration of some related problems, including vehicle selection, inventory, production planning, and reverse logistics, still has important gaps (indicated in Table 2.3). Therefore, future work should focus on the following problems:

i) Integration of supplier selection and vehicle selection with multi-sourcing, single period, multi-items for bottleneck and strategic items considering uncertainty in MTO/ ATO/ MTS production policy;
ii) Integration of supplier selection and inventory management with multi-sourcing for strategic or bottleneck items with multi-item under joint replenishment in ATO and MTS production policies;
iii) Integration of supplier selection with a single sourcing strategy, multi-period for leverage items in ATO/ MTS production policy under uncertainty;
iv) Integration of supplier selection and material flow in reverse logistics considering sustainability and distributed ledger technology adoption under uncertainty.

Furthermore, we observed that the studies engaged in supply disruptions and risks in supplier selection are still limited. Thus, future work should also address the mitigation of risks of supply associated with disruptions and other risk factors, particularly for strategic and bottleneck items, as a proactive strategy that enables firms to strengthen supply chain management - the so-called resilient supplier selection. Accordingly, developing a comprehensive methodology or solution approach to model disruptions and assess risk factors along with the mitigation strategy implementation, are required in the resilient supply chain management.

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Chapter 3

Integrated Supplier Selection under Supply Disruptions: Analytic Model Enhancement

Integration of Supplier Selection and Inventory Management Under Supply Disruptions

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Abstract In the current global market, managing supply is not a straightforward process and it becomes even more complex as uncertainty and disruptions occur. In order to mitigate their impact, the selection of suppliers of strategic items should have a more holistic view of the operations in the supply chain. We propose an integrated model for supplier selection, considering inventory management and inbound transportation. We approach this problem, incorporating stochastic demand and suppliers' imperfect quality. Imperfect quality triggers additional costs, including external failure and holding costs. Supply disruptions also affect the suppliers' lead time, resulting in delivery delays. We develop a methodology to address this challenge with simulation-optimization. A genetic algorithm determines supplier selection decisions, while inventory decisions are computed analytically. Discrete-event simulation is used to evaluate the overall performance, as well as to update the lead time dynamically, according to the disruptions. Finally, sensitivity analysis providing managerial insights reveals that criteria in supplier selection should be given a different priority depending on the characteristics of the items, and the effectiveness of disruption mitigation strategies depends on the disruption characteristics.

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Keywords: Supplier selection, order allocation, inventory management, disruptions, simulation-optimization

3.1 Introduction

As the global market is becoming increasingly dynamic and fiercely competitive, companies are forced to improve their core business capabilities, in order to ensure customer satisfaction. Supplier selection is one of the most important activities, as companies' performance and competitive advantages rely on the collaboration with capable suppliers (Wagner, 2006). More specifically, suppliers contribute to the four main competitive priorities, namely quality, delivery, flexibility, and cost (Prajogo and Olhager, 2012). For instance, the cost of materials and components, particularly for high technological products, can range from 60% to 80% of production cost (Dey et al., 2015). In addition, there might be trade-offs with other criteria. For example, one supplier may offer cheaper materials, but slightly below average quality, while another supplier may offer higher quality materials, with longer delivery lead times (Jain, Sangaiah et al., 2018). Under multiple (conflicting) criteria, supplier selection requires a careful decision-making process, which is most likely to be complex in nature.

However, not all items purchased are important to the organization. Low-value items, with abundant supply, which are not part of the company's core set of raw materials, do not have a significant impact on operations. For these non-critical items the main focus is to simplify procurement processes and make day-to-day purchases, whereby supplier selection is expeditious (Monczka et al., 2015). We can distinguish four major types of items in purchasing processes according to Klarjic's Portfolio Matrix (KPM): strategic, leverage, bottleneck, and non-critical (Caniëls and Gelderman, 2005). These four types of items differ in the complexity of supply (i.e., the degree of supply risk) and importance of purchasing (i.e., profit impacts) – c.f. Figure 1.1. Leverage items represent a relatively large share of a product's costs and relatively low supply risk, while bottleneck items are the opposite, i.e., have a low value, but may yield significant problems and risks. On the other hand, strategic items represent both a considerable value to the organization and high supply risk (i.e., the potential appearance of disruptions). Supplier selection for these strategic items should therefore be the focus of any organization. In other words, supplier selection for strategic items needs to involve a comprehensive process, considering other related activities in a supply chain in order to reduce costs, as well as to improve the other aforementioned competitive priorities (quality, delivery, flexibility).

Assessing quality is an essential step for achieving competitiveness, since the respective impacts on the firm's reputation and customer satisfaction can be significant, particularly for strategic items. The majority of the problems associated with firm's product quality is caused by the quality of incoming materials from suppliers (Feng et al., 2001). This issue affects inventory decisions and the total costs (Jaber et al., 2008; Sharifi et al., 2015). In some cases, and in order to avoid net loss, incoming imperfect materials might be kept in stock and sold as second-product categories (e.g., in the clothing industry, most of the imperfect items are sold at a discounted price; furniture stores always mark imperfect items ‘As Is’ to be sold at a reduced price). Accordingly, in practice, the resources to handle the inventory of imperfect items, such as warehouses, are usually separated from perfect items, which sustain specific holding costs for each type of item quality (Sarkar et al., 2014; Wahab and Jaber, 2010). While the importance of quality cannot be ignored, the supplier’s imperfect quality and its associated costs need to be appropriately addressed during supplier selection, including external failure costs stemming from mishandling imperfect items to customers.

Regarding delivery, an essential activity to consider in the selection procedure of strategic items’ suppliers is inbound transportation. This activity costs, on average, 50% of the total annual logistics costs of a product (Swenseth and Godfrey, 2002). Typically, a fixed price is established and charged per vehicle regardless of their transportation vehicles being partially or fully loaded. The number of vehicles used and its associated capacity determines not only the inventory investment, but also transportation costs. Hence, and taking into account the supplier’s vehicles and the efficient use of their capacity when determining the order quantity is a crucial aspect.

In addition, one of the main issues that an organization should consider is risk mitigation in general (Yoon et al., 2018), and supply risk in particular, as to improve flexibility in the reaction to unexpected disturbances. Disruptions, considered one of supply risk factors, might occur with different levels of likelihood. Some (rare) disruptions have a considerable impact and spread in the supply chain causing a ripple effect (Dolgui et al., 2020; Hosseini, Ivanov et al., 2020; Ivanov and Dolgui, 2019). For instance, the 1999 Taiwan’s earthquake created huge customer loss for many electronics companies supplied by Taiwanese manufacturers (Sheffi, 2005), and a plant fire at the Ericcson’s supplier caused 400 million Euros in lost sales (Norrman, 2004). More recently, COVID-19 outbreaks, forcing Chinese factories to shutdown, have impacted not just local or regional activities, but also global markets for many sectors, such as computers and automotive industries, resulting in reduced productivity and disruptions in the supply chain (Yu and Aviso, 2020). Other, more frequent disruptions, although not as devastating, need to be carefully addressed, as their cumulative impact can be quite significant. This is particularly true for strategic items (e.g., chipsets in the electronic industry). However, for non-critical items with an abundant source, high number of suppliers, and substitution (e.g. standard screws in the electronic industry), the respective impact can be less significant (Montgomery et al., 2018). Therefore, determining disruption mitigation strategies is especially relevant for strategic items.

Disruption mitigation strategies in the supply chain can be categorized according to proactive and reactive strategies (Dolgui et al., 2018; Snyder et al., 2016). Proactive strategies, dealing with the implementation of supply chain protection actions without necessarily considering recovery measures, can be addressed in several ways, including inventory buffers, capacity buffers, and backup facilities (Dolgui et al., 2018; Snyder et al., 2016; Tomlin, 2006). In reactive strategies, where designing SC processes and structures can be adjusted when disruptions occur, operational contingency (such as multi or backup sourcing and shipping routes), can be considered (Dolgui et al., 2018; V. Gupta and Ivanov, 2020; He et al., 2020; S. Li et al., 2017; Tomlin, 2006).

In order to fully consider these different competitive dimensions (costs, quality, delivery and flexibility), and to address the trade-offs between them, integrating supplier selection with other supply chain activities is essential. Supplier selection has been widely studied in the literature, focusing on the integration of other activities at either tactical or operational levels of a supply chain, including order allocation, inventory management, and transportation. Although the literature on supplier selection is substantial, the number of studies successfully addressing the complexity of strategic items is relatively small. Most of the studies consider supplier selection and order allocation (e.g. Arikan (2013), Kannan et al. (2015), Jadidi et al. (2015), Yousefi et al. (2017)), but disregard inventory management, transportation and supply uncertainty. In fact, strategic items require assurance of supply while maintaining low costs through integrated supplier selection and inventory management under multi-sourcing strategy (Firouz et al., 2017). Firouz et al. (2017), Keskin et al. (2010), and Saputro et al. (2019) are some of the few to consider disruptions and integrate those entire activities in supplier selection processes. However, some pivotal aspects need to be addressed and fully incorporated, in order to achieve competitive priorities as a whole, particularly when dealing with the supply of strategic items.

The previous studies focused on this complex integration via mathematical programming and simulation-optimization (S-O). Although S-O have proved to be effective in dealing with complex features, such as disruptions and their impact on the lead time, simulation was only used to assess the total costs more accurately (as an evaluation function) (Firouz et al., 2017; Hlioui et al., 2017; Keskin et al., 2010; Saputro et al., 2019). In other words, inventory decisions, which are calculated analytically and through parameters such as lead time, were not properly corrected according to the information on disruption.

We contribute to the existing literature by proposing a comprehensive model, as well as developing a novel solution approach. First, we propose a model that integrates supplier selection and inventory management under multi-sourcing, considering all key features to properly address strategic items under the main competitive priorities. Second, we promote the development of a simulation-optimization (S-O) method focused on a complex problem, which improves the methods of past studies, in order to efficiently and effectively address the issue. Simulation is used not only as a better (more accurate) evaluation function, but also to refine parameters (i.e., lead time) in the optimization model, so that better decisions can be computed. In addition, managerial insights also contribute to the pioneer aspects of the current study. We provide insights to understand the impact of different types of disruptions (i.e., frequent, yet short and rare but long) on the total costs. We also carry out the analysis of supplier selection criteria for fast and slow-movers, in order to understand their impact on the decisions and total costs, and to identify the most influential criteria in supplier selection.

This paper also includes other important sections. We provide a literature review in Section 2, emphasizing the models that have been proposed for the integration of supplier selection and inventory management. The research gaps are also addressed. In Section 3, we present the model development phases involving problem definition and model formulation. Section 4 focuses on the proposal of a solution approach based on S-O. In this solution approach, parameter refinement is developed to incorporate dynamic lead time as a function of disruptions. Computational results presented in Section 5 focus on the benefits of the implementation of a of solution approach. In addition, managerial insights are provided in Section 6 to understand the impact of critical aspects of supplier selection and underlying trade-offs, including imperfect quality, vehicle capacity, and lead time on the total costs, as well as on the decisions. This section also explores how disruptions can be characterized and modeled in a sensible way and how the risk mitigation strategy can be applied using a sophisticated approach. The final section of the paper, summarizes the most important insights of the study.

3.2 Literature

In competitive industries, cooperation with suppliers attracts manufacturing firms to gain long-term benefits. The success of the cooperation largely depends on a selective process in choosing appropriate suppliers. For items that represent a considerable value to the firm, and high supply risk, the so-called strategic items, supplier selection becomes a strategic initiative that requires careful consideration within supply chain management (Caniëls and Gelderman, 2005). In this context, it is essential to integrate supplier selection with other activities, including inventory management.

Integration of supplier selection and inventory management has received massive attention in the literature (Firouz et al., 2017; Guo and X. Li, 2014; Hlioui et al., 2017; Jain, Kundu et al., 2015; Keskin et al., 2010; Saputro et al., 2019; Zarindast et al., 2017). Guo and X. Li (2014) addressed an integrated supplier selection problem under a stochastic inventory system incorporating demand variability. In their study, suppliers' uncertainty was not taken into account. Jain, Kundu et al. (2015) considered stochastic lead time in the integration of supplier selection and inventory management. The lead time of each supplier was considered singular and uncertain. Hlioui et al. (2017) addressed supplier selection and inventory management by considering the unreliability of inspection lot, due to the variability of suppliers' quality. The inventory decisions were determined via the review system (s, Q). However, this study was limited to the selection of two suppliers without taking into account the order allocation. Zarindast et al. (2017) incorporated the changes in purchasing price as the result of currency fluctuation in supplier selection. Keskin et al. (2010) and

Firouz et al. (2017) addressed the integrated supplier selection, the incorporation of stochastic demand into inventory and suppliers' quality. According to the inventory review system (Q, R), this study attempted to select suppliers and determine inventory decisions. Saputro et al. (2019) also integrated supplier selection with inventory management with stochastic demand.

Besides, another issue that significantly influences the business operation and strategic enterprise performance, as well as the stabilization, is the occurrence of disruptions (Ivanov and Dolgui, 2020). Mitigating the risk of supply disruptions is crucial to prevent a more significant impact on the entire supply chain, which can be high for strategic items. It entails a proactive strategy (Snyder et al., 2016), as well as proper supplier selection (Tomlin, 2006). Unfortunately, most of the studies on supplier selection, particularly those integrating inventory management, disregarded supply disruptions (Guo and X. Li, 2014; Hlioui et al., 2017; Jain, Kundu et al., 2015; Zarindast et al., 2017). The distinguishing studies presented by Saputro et al. (2019), Keskin et al. (2010), and Firouz et al. (2017) attempted to mitigate the risk of supply disruptions through appropriate supplier selection and inventory replenishment. Disruptions were considered a factor affecting delivery delays. Every time disruptions occur, the lead time becomes higher than the stated lead time. Nevertheless, the lead time variability due to disruptions was neither refined nor updated when determining reorder point.

Simulation has been successfully used to study disruptions in the supply chain (Ivanov, 2017; Ivanov and Rozhkov, 2019). The extension of this approach, namely simulation- optimization (S-O), has been introduced in the literature. Figueira and Almada-Lobo (2014) classified simulation-optimization approaches based on four dimensions, including simulation purpose, hierarchical structure, search method, and search scheme. According to the simulation purpose, there are three major simulation approaches that can be categorized into evaluation function (EF), analytical model enhancement (AME), and solution generation (SG). Some of the previous studies applied S-O to tackle supplier selection problems. Keskin et al. (2010) and Firouz et al. (2017) developed an S-O approach in order to incorporate uncertainty and represent disruptive events. The evaluation function (EF), which involves iterative procedures and simulation to evaluate solutions and guide search, was applied to solve the issue at hand. A scatter search was used to optimize supplier selection. An S-O approach, also based on the EF, was developed by Hlioui et al. (2017) to tackle an integrated supplier selection problem. Unlike Keskin et al. (2010) and Firouz et al. (2017), the solution approach was performed sequentially, where simulation was run first, followed by optimization. First, data from several simulation runs were collected to perform a design of experiments. Subsequently, the response surface methodology was used for optimizing parameters according to the relationship between the suffered costs and the significant main factors, and interactions.

Nevertheless, the S-O proposed by the previous studies presents significant issues, particularly the enhancement and the exclusion of parameter refinement. Incorporating the disrupted lead time can be considered an important strategy in disruption risk management (Mohebbi, 2003). The refinement requires a sophisticated approach, and it is found to remain undeveloped, particularly in the aforementioned studies. Thus, developing a solution approach with refinement (i.e., lead time) is one of the major contributions of our study. Our challenge is to develop an S-O approach to improve decisions through parameter refinement. Other studies that did not consider disruptions, such as Guo and X. Li (2014), Jain, Kundu et al. (2015), Zarindast et al. (2017), and Hlioui et al., 2017 cannot be compared to our study in terms of the solution approach, since they failed to address this complex problem.

Furthermore, some essential aspects related to supply have been disregarded in the studies mentioned above, particularly dealing with imperfect quality and vehicle capacity, which may affect the total cost incurred in the system. Imperfect quality might additionally involve an opportunity cost. Indeed, the consequences of imperfect quality not only relate to the costs incurred in the shop floor as a result of defects or as additional costs for inspection, repair, material handling, but also to customer satisfaction (Miguel and Pontel, 2004). The transportation fares are generally charged according to the number of vehicles. Utilizing vehicle capacity (truckload) for shipping orders from suppliers may yield significant cost savings to the firm. From the practitioners' point of view, service transportation procurement, particularly for TL (full truckload) vehicles, is critical, since it can extensively affect the overall business operating costs (Basu et al., 2015). Therefore, considering imperfect quality and vehicle capacity when making decisions, either strategic or tactical, provides an opportunity to further improve operational efficiency.

Our study fills the gaps in the literature by considering imperfect quality and vehicle capacity, as well as their associated costs in the context of a comprehensive decision-making problem. We also contribute a novel solution approach for supply risk mitigation by refining the affected parameter by using the output of simulation according to the disruption characteristics and providing simultaneous decision making for supplier selection and inventory management. Finally, Table 3.2 compares several studies with the proposed study, focusing on several features of the underlying issues, such as uncertainty, disruption, transportation policy, and cost component.

Table 3.1: Problem features of integrated supplier selection and inventory management

Study	Uncertainty	Disruptions		VC	Cost Component				Approach
		Parameter	Refinement		PC	IC	TC	IQC	
Keskin et al. (2010)	Demand Quality (perfect)	Lead Time	No	No	✓	✓	✓	-	S-O
Guo and Li (2014)	Demand	-	N/A	No	✓	✓	-	-	MP
Jain et al. (2015)	Lead Time	-	N/A	No	✓	✓	✓	-	M
Firouz et al. (2017)	Demand Quality (perfect)	Lead Time	No	No		✓	✓	-	S-O
Zarindast et al. (2017)	Price	-	N/A	No	✓	✓	✓	-	MP
Hlioui et al. (2018)	Inspection Lot	-	N/A	No	✓	✓	-	-	S-O
This Study	Demand Quality (perfect & imperfect)	Lead Time	Yes	Yes	✓	✓	✓	✓	S-O

Abbreviation:
VC: Vehicle Capacity | PC: Purchasing Cost | IC: Inventory Cost | TC: Transportation Cost | IQC: Imperfect Quality Cost | S-O: Simulation-Optimization | MP: Mathematical Programming | M: Metaheuristics

3.3 Model Development

3.3.1 Problem Definition

In this study, we consider a supply network of several suppliers and one buyer, in addition to multiple geographically distributed plants. More specifically, there are n plants which source a single item from two or more of m suppliers to meet plant-specific demand (shown in Figure 3.1). Stochastic demand arrives at each plant according to a specific distribution with a plant-specific mean μ_i and deviation $\sigma_i, i \in I = (1, ..., n)$. Once a supplier is selected $(X_j = 1, j \in J = (1, ..., m))$ to supply the material, plants have to pay fixed contractual costs f_i. Furthermore, each supplier offers a unit purchasing price c_j whenever the order of each plant is allocated to a supplier (Y_{ij}). Since suppliers have a specific capacity (w_j), plants cannot purchase a material which exceeds the suppliers' capacity. In other words, order allocation for each supplier should respect the supply capacity. The proposed model is formulated based on the notation shown in Table 3.2, indicating sets, indexes, parameters and decision variables.

Table 3.2: Input parameters and decision variables

Notation	Description
Indices	
i	: index for plant, $i = 1, 2, \ldots, n$
j	: index for supplier , $j = 1, , \ldots, m$
Parameters	
$E[D_i]$	: Expected annual demand of plant i
a_i	: External failure costs per unit for imperfect items of plant i
o_i	: Setup costs of plant i
h_i	: Holding costs per unit for perfect items of plant i
h'_i	: Holding costs per unit for imperfect items of plant i
s_i	: Shortage costs per unit and per time of plant i
f_j	: Fixed annual contractual costs of supplier j
c_j	: Purchasing costs per unit of supplier j
k_j	: Rate of imperfect quality for supplier j
b_j	: Annual supply capacity of supplier j
u_j	: Capacity of a TL vehicle for supplier j
θ_j	: Disruption frequency rate for supplier j
v_j	: Disruption length for supplier j
$E[LTD_{ij}]$	: Expected lead time demand between plant i and supplier j
$\eta[LTD_{ij}, R_{ij}]$	: Standardized loss function between plant i and supplier j
p_{ij}	: Fixed transportation costs per replenishment from supplier j to plant i
r_{ij}	: Transportation costs per mile and per replenishment from supplier j to plant i
d_{ij}	: Distance between plant i and supplier j
l_{ij}	: Lead time between plant i and supplier j
Decision variables	
X_j	: 1, if supplier j is selected; 0, otherwise
Y_{ij}	: Purchase amount allocated by plant i to supplier j
Q_{ij}	: Order quantity of plant i to supplier j
R_{ij}	: Reorder point of plant i to supplier j

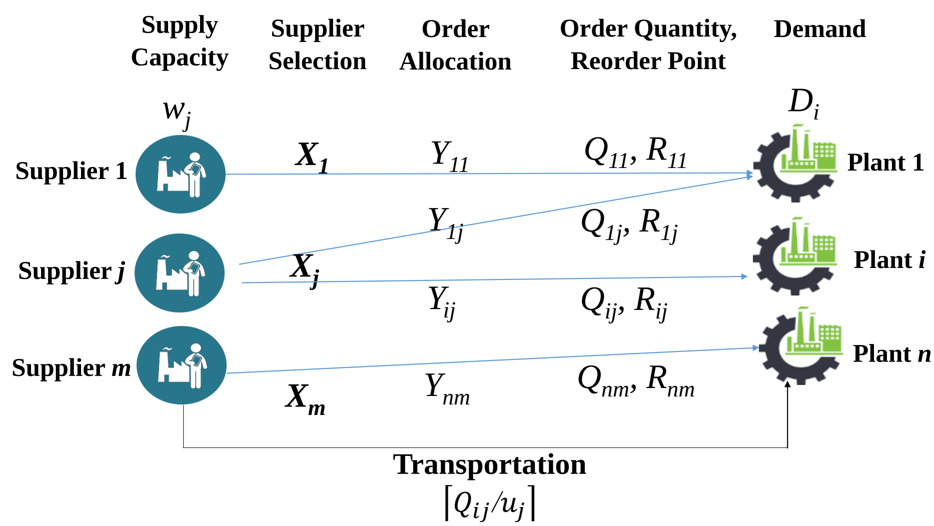


Figure 3.1: Network supply between plants and suppliers

According to a (Q, R) policy, inventory levels are continuously reviewed by placing an order with fixed quantity (Q), as soon as the inventory level drops to or below a reorder point (R). In this study, we assume that each plant $i \in I$ follows a specific order quantity Q_{ij} and reorder point R_{ij} for each associated source, in order to meet order allocation Y_{ij}. Since the distance between each plant and each supplier varies according to their location, we consider a supplier-plant specified lead time l_{ij}.

Thus, the order Q_{ij} arrives at plant i after a supplier-plant specified lead time l_{ij}. In terms of inventory system costs at plant $i \in I$, each replenishment from a plant carries setup costs (o_i) and inventory carrying costs per unit and per unit of time (h_i). Additionally, if stock outs occur at plant i, there are shortage costs $s_i, i \in I$, per unit and per time.

In case TL vehicles are used for inbound transportation, plants are charged based on the number of the vehicles used for said purpose. It is assumed that each supplier provides a single vehicle type with a capacity of u_j units. We depict transportation costs corresponding to each order delivery between suppliers and plants according to TL transportation vehicles, including fixed transportation costs p_{ij} and mileage costs $r_{ij}.d_{ij}$. The TL expenses depend on the delivery distance and generally do not consider the respective amount. Therefore, unit transportation costs in case of TL transportation are not considered in this situation. The total transportation costs paid for shipping an order of Q units for each supplier to each plant equals $\lceil Q_{ij}/u_j \rceil (p_{ij} + r_{ij}d_{ij})$.

We propose a model for supplier selection combined with inventory management, which incorporates imperfect quality and disruptions. We assume that each delivery order includes not only perfect quality items but also imperfect ones with a proportion of k_j. The imperfect rate (k_j) is a stochastic parameter, and only its distribution can be estimated by the manager. Rather than considering purchasing and inventory costs exclusively, supplier selection and inventory decisions are also determined based on the costs of imperfect quality introduced to the model. In general, holding costs cover some expenses, such as rent for the required space, equipment costs, insurance and security, and material handling costs. Regarding inventory management, the annual interest rate is commonly computed based on those costs. In the manufacturing environment, imperfect items are usually stored separately from perfect items, namely in a different warehouse. Therefore, the values of the annual interest rate are not identical for perfect and imperfect items. As a result, the holding costs of perfect (h_i) and imperfect items (h'_i) differ (Sarkar et al., 2014; Wahab and Jaber, 2010). The inventory of imperfect items remains constant over time, since it is not used to meet demand on a regular basis. Moreover, said items will only be sold when a new order is placed. Although perfect and imperfect items are separated, failures in the handling or sorting processes can still occur due to human errors. Accordingly, each plant faces external failure costs for each unit (a_i) due to liability or complaints by customers acquiring imperfect items. Indeed, and although most imperfect items are separated from others before shipping (and sold as a second-product category), some will still reach the customer. Therefore, there is a reduction of the company's reputation as a result of product failures after delivery to the customer (Miguel and Pontel, 2004). This represents a perceived non-value-added activity that affects the customer's buying experience and compromises the company's reputation.

Furthermore, disruptions at suppliers affect other aspects like reorder points, since the actual observed lead time and corresponding lead time demand would be higher than the stated lead time. Thus, we incorporate the lead time l_{ij} whenever disruptions occur to determine the reorder points R_{ij} through refinement undertaken by the proposed solution approach detailed in Section 4.

The following assumptions are used:

1. Transportation costs associated with a TL vehicle. Each supplier provides a single vehicle type with a specific load capacity (u_j);
2. Each lot purchased (Q_{ij}) contains imperfect items with the percentage (k_j);
3. The imperfect items in each lot (Q_{ij}) are kept in stock and removed for sale when the new order is placed. Hence, imperfect holding costs per unit (h'_i) exist in each lot purchased;
4. 100% screening process is conducted by the plants once the order arrives. The screening time for purchased items is fast and will be neglected;
5. Due to the purchase of imperfect items, there could be external failure costs per unit (a_i);
6. Unsatisfied demand due to disruptions will result in lost sales.

3.3.2 Model Formulation

This study led to the development of a single item, single period and multi-sourcing model under TL policy for the integration of supplier selection and inventory management, incorporating imperfect quality and disruptions. The proposed model includes an objective function which minimizes average annual total costs associated with supplier selection related costs (contractual fees and purchasing costs), plant inventory costs (holding, setup, and shortage costs), TL transportation cost (fixed and mileage costs), and imperfect quality-related costs (external failure and imperfect items' holding costs).

The objective function and constraints of the model are presented as follows.

Objective: Min Z =

$$\sum_{j=1}^{m} f_j X_j + \sum_{i=1}^{n}\sum_{j=1}^{m} c_j Y_{ij} \tag{6.1}$$

$$+\sum_{i=1}^{n}\sum_{j=1}^{m} \frac{o_i Y_{ij}}{Q_{ij}(1-E[k_j])} + \sum_{i=1}^{n}\sum_{j=1}^{m} h_i \left(\frac{Q_{ij}(1-E[k_j])}{2} + R_{ij} - E[LTD_{ij}]\right) \tag{6.2-a}$$

$$+\sum_{i=1}^{n}\sum_{j=1}^{m} s_i \eta(LTD_{ij}, R_{ij}) \frac{Y_{ij}}{Q_{ij}(1-E[k_j])} \tag{6.2-b}$$

$$+\sum_{i=1}^{n}\sum_{j=1}^{m} \frac{(p_{ij} + r_{ij} d_{ij}) \lceil \frac{Q_{ij}}{u_j} \rceil Y_{ij}}{Q_{ij}(1-E[k_j])} \tag{6.3}$$

$$+\sum_{i=1}^{n}\sum_{j=1}^{m} a_i Y_{ij} E[k_j] + \sum_{i=1}^{n}\sum_{j=1}^{m} h'_i Q_{ij} E[k_j] \tag{6.4}$$

Subject to:

$$\sum_{j=1}^{m} Y_{ij} = E[D_i], \quad \forall i \in I \tag{6.5}$$

$$\sum_{i=1}^{n} Y_{ij} \leq b_j X_j, \quad \forall j \in J \tag{6.7}$$

$$Y_{ij} \geq 0, \quad Q_{ij} \geq 0, \quad X_j = 0 \; or \; 1, \quad \forall i \in I, \;\; \forall j \in J \tag{6.8}$$

In the objective function, the form (6.1) represents supplier contractual costs and the average annual purchasing costs. The average annual inventory costs (6.2-a, 6.2-b) are calculated based on setup, holding, and shortage costs. $\eta(.,.)$ in (6.2-b) represents the standard loss function. Furthermore, form (6.3) represents the average annual transportation costs under TL policy with vehicle capacity u_j. The costs per vehicle are measured based on the fixed vehicle charge and mileage costs. The distance between suppliers and plants is measured according to Euclidean measure associated with suppliers' coordinates d_j and plants' coordinates d_i. The costs associated with imperfect quality (6.4) are composed of the average annual external failure costs and imperfect holding costs, calculated according to the expected imperfect rate ($E[k_j]$). $E[k_j]$ is computed according to a particular distribution; more specifically, it is perceived as uniformly distributed. Regarding constraints, equation (6.5) assures that demand at each plant must be satisfied from the order allocation of selected suppliers. Equation (4.6) ensures that the order allocation should not exceed the suppliers' annual supply capacity. Finally, equation (4.7) represents non-negativity and binary decision variables.

3.4 Solution Approach

Stochastic demand and disruptions occurring and related to this integrated problem need to be modeled realistically for a close estimate of total costs. Simulation is used to represent the disruptions associating frequency and duration, since it encourages active and complete experimentation with various possible policies under a variety of different settings (Melnyk et al., 2009); moreover, simulation has proved to a suitable tool for analysis under dynamic environments (Saputro et al., 2019). Therefore, we use simulation-optimization to improve the decisions in these environments. Contrary to S-O approach proposed by Firouz et al. (2017), Keskin et al. (2010), and Saputro et al. (2019), which uses simulation just as an evaluation function (EF), we develop an S-O approach where simulation's feedback is used to refine parameters in the analytical model. In our case, this analytical model enhancement (AME) approach refines the lead-time, in order to address possible delays that result from disruptions.

We use a nested algorithm based on a genetic algorithm (GA) to search within the solution space. GA is applied due to its advantages in solving combinatorial optimization problems effectively with sparse solution spaces (McGovern and S. M. Gupta, 2007), and problems that are complex and loosely defined (Lee et al., 2013). With GA, falling into a local minimum permanently can be avoided with the inclusion of the random changes in solutions (Adánez et al., 2019). A simulation model runs as a stochastic evaluator of the solution. In the solution procedure, the GA evaluates decision variables of X (suppliers) based on the total costs formulated in the objective function (Z). Given the value of X, the nested procedure is initialized by determining order allocation (Y) according to the transportation costs. According to the allocation, we then determine inventory decisions associated with order quantity (Q) and reorder point (R), which are calculated by using analytical expressions. The solutions containing supplier selection (X) and inventory decisions (Q, R) are then passed to the simulation incorporating demand uncertainty and disruptions for objective function evaluation (Z). According to these variables, the performance measure (Z) is returned to the optimization. The GA then uses this performance measure to optimize the solutions. This solution procedures depict the EF approach, which is illustrated in Figure 3.2.

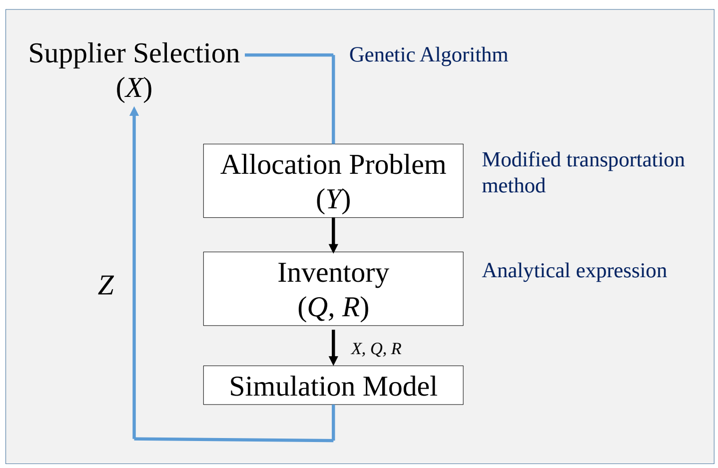


Figure 3.2: The initial approach: using simulation as the evaluation function (EF)

We extend the previous solution procedures (proposed by Saputro et al. (2019)) by using the simulation's feedback also to refine parameters in the analytical model, the so-called AME. These solution procedures will be used in comparison to the previous solution procedure in Section 5.2. Using AME, simulation is employed to estimate the lead time (L) incorporating the disruptions. The refinement procedure begins such way that, for every randomly selected X, and for each replication, the lead time derived from simulation based on the mean value is sent for optimization. According to the refined lead time, the reorder point is recalculated. In our study, we iterate this refinement with k iterations, so that it converges (convergence is actually achieved in the first iterations most of the time). Similar to the EF, GA optimizes the variable of X according to the total cost (Z) derived from the simulation incorporating demand uncertainty and disruptions. Figure 3.3 illustrates the solution procedure of the proposed AME.

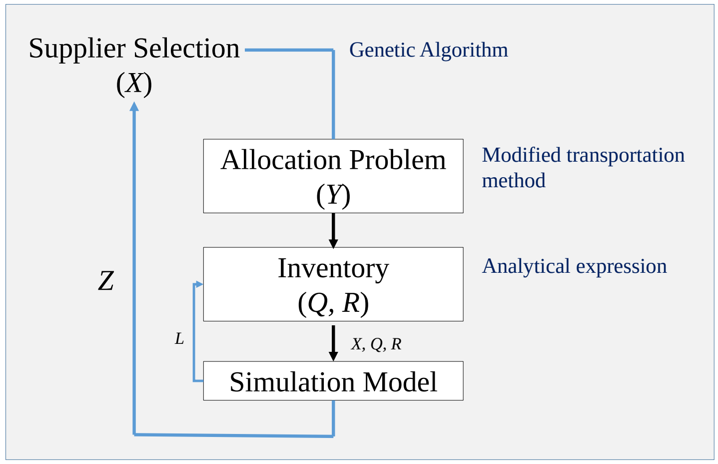


Figure 3.3: The proposed approach: using simulation to enhance the analytical model (AME)

3.4.1 Order Allocation Problem

Given the value of X which is randomly selected, we determine order allocation (Y) according to the transportation cost given by (1c) in the objective function and the constraints (6.5) and (4.6). More specifically, we solve the the following problem by using a transportation method:

$$\min_{Y} \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{(p_{ij} + r_{ij} d_{ij}) \lceil \frac{Q_{ij}}{u_j} \rceil Y_{ij}}{Q_{ij}(1 - E[k_j])}$$

s.t

$$\sum_{j=1}^{m} Y_{ij} = E[D_i], \qquad \forall i \in I$$

$$\sum_{i=1}^{n} Y_{ij} \leq b_j X_j, \qquad \forall j \in J$$

$$Y_{ij} \geq 0 \qquad \forall i \in I, \quad \forall j \in J$$

The order quantity for each plant, represented by Q_{ij} in this sub-problem is calculated based on the equal dispersed estimation. By using the classical EOQ, the order quantity is scaled according to the number of suppliers to obtain a better estimation of the number of trips and accordingly, the transportation cost. For each plant $i \in I$, the order quantity is calculated by using the following equation.

$$Q_{ij} = Q_{ij}^{\dagger} = \frac{\sqrt{\frac{2 o_i E[D_i]}{h_i}}}{m} \tag{6.6}$$

where m denotes the number of suppliers.

3.4.2 Inventory Problem

The inventory decisions, including order quantity (Q) and reorder point (R), are determined once the order allocation (Y) is obtained. Due to multi-sourcing, compartmentalization is considered for inventory management. In other words, inventory decisions for a supply duo (plant-supplier) corresponding to the order quantity (Q_{ij}) and reorder point (R_{ij}) lead to a non-identical value. The lead time depends on the distance between a supplier and a plant. Thus, it is necessary to determine specific inventory decisions for each supply duo, as the distance varies among suppliers. Under a review system (Q, R), a reorder point is estimated according to the lead time demand. Since the lead time demand depends on the supplier lead time, the reorder point (R_{ij}) would also follow a specific value for each supply duo.

Given the value of Y, the optimal order quantity from a plant to a supplier (Q_{ij}) is obtained according to inventory costs given by (**??**), (6.3), and imperfect items' holding costs (1d). However, a classical EOQ equation is not appropriate for this problem due to imperfect quality and TL vehicle capacity. Hence, we use a heuristic proposed by Toptal et al. (2003) as the extension of EOQ, according to the TL policy (see Algorithm 1). In Algorihtm 1, n_{ij} represents the number of vehicles. Given n_{ij}, Q'_{ij} (an EOQ considering shortage and transportation costs) is then computed, based on the vehicles' capacity (u_j). If Q'_{ij} is greater than or equal to $(n_{ij} + 1)u_j$, then the order quantity is either $n_{ij}u_j$ or $(n_{ij} + 1)u_j$, depending on which yields lower total costs (Z). Otherwise, it is either Q'_{ij} or $n_{ij}u_j$.

Algorithm 1: CompOrderQty ***(n)***

for $i \in I$ ***and*** $j \in J$ **do**

  $Q_{ij} = \sqrt{\frac{2o_iY_{ij}}{\left(h_i(1-E[k_j])+2h'_iE[k_j]\right)(1-E[k_j])}}$

  $n_{ij} \in \mathbb{Z}^+ : n_{ij}u_j < Q_{ij} \leq (n_{ij}+1)u_j$

  $Q'_{ij} = \sqrt{\frac{2(o_i+s_i\eta(LTD_{ij},R_{ij})+(n_{ij}+1)(p_{ij}+r_{ij}d_{ij}))Y_{ij}}{\left(h_i(1-E[k_j])+2h'_iE[k_j]\right)(1-E[k_j])}}$

  if $Q'_{ij} \geq (n_{ij}+1)u_j$ **then**

    $Q^*_{ij} = \underset{Q\in\{n_{ij}u_j,\ (n_{ij}+1)u_j\}}{\operatorname{argmin}} Z(Q)$

  else

    $Q^*_{ij} = \underset{Q\in\{n_{ij}u_j,\ Q'_{ij}\}}{\operatorname{argmin}} Z(Q)$

  end

end

return $Q = Q_{ij}$, $i \in I$ and $j \in J$

If $Q^*_{ij} = Q'_{ij}$, in the continuous review systems, determining the optimal (Q_{ij}, R_{ij}) involves a trade-off between perfect and imperfect holding, shortage, and transportation costs. Thus, R_{ij} is solved by using (6).

$$R_{ij} = F^{-1}\left(1 - \frac{Q'_{ij}h_i}{s_i Y_{ij}}\right) \tag{6}$$

3.4.3 Simulation Framework

A discrete event simulation model is built according to the supply network illustrated in Figure 3.4. Five events are created to represent inventory control under a multi-sourcing strategy, which can be classified as ordering and demand signaling, receiving order, stockouts, cost estimation, and disruptions.

Ordering and demand signaling (A) indicates the need to schedule replenishment based on the continuous review policy (Q, R). Stochastic demands are generated to initialize the order allocation representing multi-sourcing. Inventory levels are routinely checked to ensure whether replenishment needs to be performed or not. Since imperfect items are kept as stock, the inventory levels for imperfect and perfect items are always updated. Replenishment is only scheduled when the inventory levels, particularly of the perfect items, reach the reorder point (R). Accordingly, the amount Q is ordered to the suppliers. The next order will be generated if inventory levels reach the reorder point and there is no other order in-transit indicated in (B).

Receiving order (B) is used for scheduling the order arrival within the lead time. When the order arrives, the inventory levels increase. At that moment, there is no other order assigned to suppliers. This event also gives a signal to (A) to ensure that there is no order in-transit. The amount of order received from a supplier includes perfect items ($Q_{ij}(1 - E[k_j])$) and imperfect items ($Q_{ij}E[k_j]$).

Stock outs (C) occur whenever inventories on-hand are below zero. Stock outs lead to shortage costs. The shortage costs are computed at the end of the planning horizon.

Cost estimation (D) includes several cost components such as purchasing, external failure, inventory holding for perfect and imperfect items, setup, and transportation costs. Those costs components are computed annually within the planning horizon.

Disruptions (E) are modeled based on the degree of severity and occurrence. Disruptions are scheduled based on a Poisson process with θ_j and length v_j. They are only revealed at the moment they occur, and they influence the suppliers' ability to fulfill the orders. When disruptions occur, the order fulfillment is delayed and the lead time is higher than the stated lead time. This disruption event affects (A) and (B), mainly the replenishment and order arrival, due to the dynamic lead time as a function of the disruptions. Consequently, the inventory levels keep decreasing during that time.

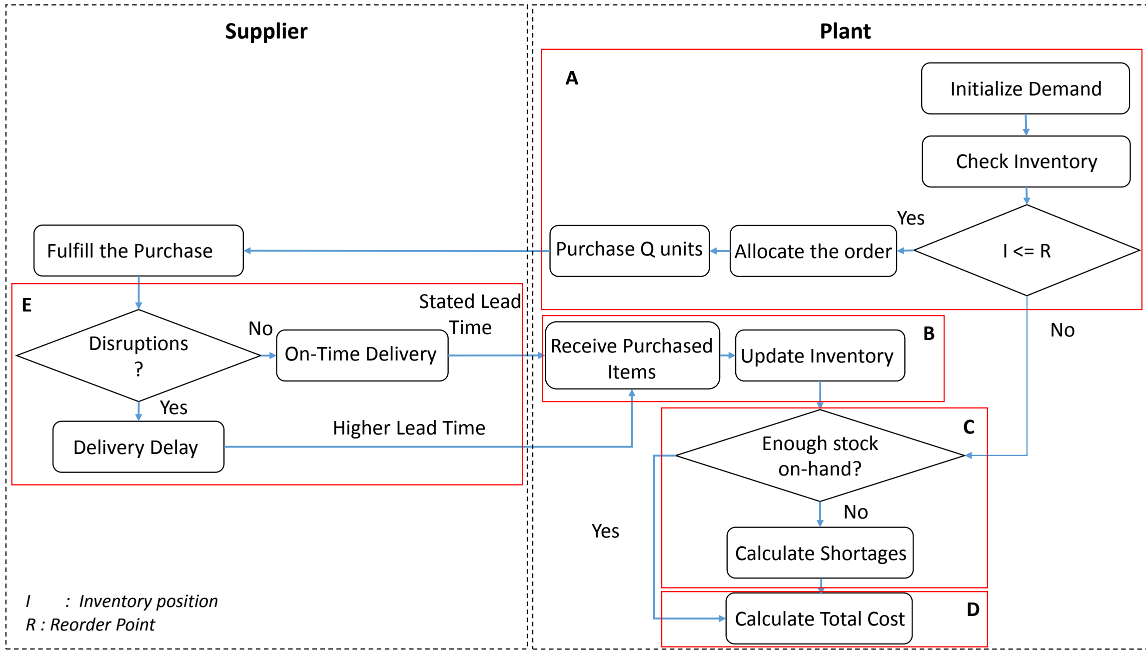


Figure 3.4: An illustration of a simulation for a network supply between a plant and suppliers

3.5 Computational Results

3.5.1 Experimental Setup

In this experiment, two problems are created, and each includes a firm with eight manufacturing plants and ten suppliers. The models are run with ten replications, each according to a five-year period †. We consider strategic items which have a significant impact on profit, thus indicating the respective high annual consumption value. In order to represent this type of items, we generate demand as an input of simulation for each manufacturing plant, which follows a particular distribution. For fast-moving items, whose purchasing costs are relatively low, the Normal distribution is used, with specified μ_i and σ_i. For slow-moving (expensive) items, in order to capture different skewness, a Poisson distribution with demand rate λ_i is selected. These are the typical distributions used to represent these types of items (Silver et al., 2017).

For the fast movers, we adopt some parameters from Firouz et al. (2017). The parameters' values for the slow movers are determined based on other studies which are relevant or subject to a case study, such as demand (Chang et al., 2001), holding cost (Nasri et al., 2008), shortage cost (Hishamuddin et al., 2012), imperfect rate, imperfect item's holding costs (Sarkar et al., 2014), external failure costs (Chiu et al., 2007), supply capacity (Ozkok and Tiryaki, 2011), vehicle capacity, and unit

†Preliminary tests revealed that these parameters would provide total cost values within an error margin of 2%, with a 95% confidence level.

purchasing costs (Jafari Songhori et al., 2011). We introduce some new parameters concerning imperfect quality and TL transportation, namely external failure costs (a_i), imperfect items' holding costs (h'_i), imperfect rate (k_j), and vehicle capacity (u_j).

Table 3.3 shows the input parameters for the base case used in the experiments. The experiments are run on a computer with a 1.90 GHz processor and 4 GB of RAM. Simulation models are built in AnyLogic 8.0.

The tuned parameters of GA are initialized, including population initialization, which is generated randomly with population size 100, crossover with probability 0.80, and mutation with probability 0.15. A tournament selection is used for the selection. The fitness function is determined according to the total costs associated with the objective function. This objective function is derived from the simulation in each iteration of simulation-optimization. The algorithm is terminated when a maximum number of generations is reached, fixed to 1000 generations.

Table 3.3: Input parameters for the base case

Parameters		Values		Units
		Fast movers	Slow movers	
Plant, $i \in I$				
Demand	μ_i, σ_i; λ_i	: U(1000, 3000), U(150, 300)	U(40, 100)	unit/year
Setup costs	o_i	: U(500, 1000)	U(500, 1000)	\$/order
Holding costs	h_i	: U(0.5, 3.0)	U(10, 15)	\$/unit/year
Shortage costs	s_i	: U(5.0, 10.0)	U(30, 50)	\$/unit/year
Imperfect items' holding costs	h'_i	: U(0.25, 1.5)	U(5, 7.5)	\$/unit/year
External failure costs	a_i	: U(0.2, 1)	U(6.25, 12.25)	\$/unit
Location		: [U(0, 500), U(0, 500)]	[U(0, 500), U(0, 500)]	
Supplier, $j \in J$				
Supply capacity	b_j	: U(7500, 10000)	U(100, 300)	unit
Imperfect rate	k_j	: U(0.15, 0.35)	U(0.10, 0.20)	
Vehicle capacity	u_j	: U(150, 300)	U(60, 90)	unit/vehicle
Disruption frequency	θ_j	: U(1, 7)	U(1, 7)	days
Disruption length	v_j	: U(0.5, 2)	U(0.5, 2)	days
Contractual costs	f_j	: U(50000, 100000)	U(10000, 17000)	\$
Unit purchasing costs	c_j	: U(0.4, 2.0)	U(25, 60)	\$/unit
Location		: [U(0, 500), U(0, 500)]	[U(0, 500), U(0, 500)]	
Plant-Supplier, $i \in I, j \in J$				
Fixed transportation costs	p_{ij}	: U(250, 500)	U(250, 500)	\$/order/vehicle
Variable transportation costs	r_{ij}	: U(0.75, 3)	U(0.75, 3)	\$/mile/vehicle
Lead time	l_{ij}	: $\left(\frac{U(1,2)}{60}\right)d_{ij}$	$\left(\frac{U(1,2)}{60}\right)d_{ij}$	hours

3.5.2 Performance Evaluation of Solution Approaches: AME vs EF

To emphasize the advantage of our solution approach, particularly in refining the lead time, we compare our solution approach to the S-O against the EF. For the comparison process, the problems are solved using the same settings from the base case. Compared to the EF, the proposed AME results in better quality with 5.2% and 4.1% improvement for the fast and slow movers, respectively. By using the EF approach, the simulation model runs as a stochastic evaluator of the solution without updating the lead time; in this sense, the respective reorder point is not improved.

The proposed approach can lead to improvement due to the lead time refinement; therefore we can benefit from having a better estimated reorder point that advances supplier selection decisions and reduces total costs. In other words, this approach brings technical support for the success of proactive strategy implementation in mitigating the risks of supply disruptions.

Furthermore, we also analyzed the strengths of the proposed approach when changing key parameters. For this purpose, we perform a sensitivity analysis on plants-related parameters, including shortage, holding, and setup costs. All parameters increase and decrease in steps of 10% up to 40%.

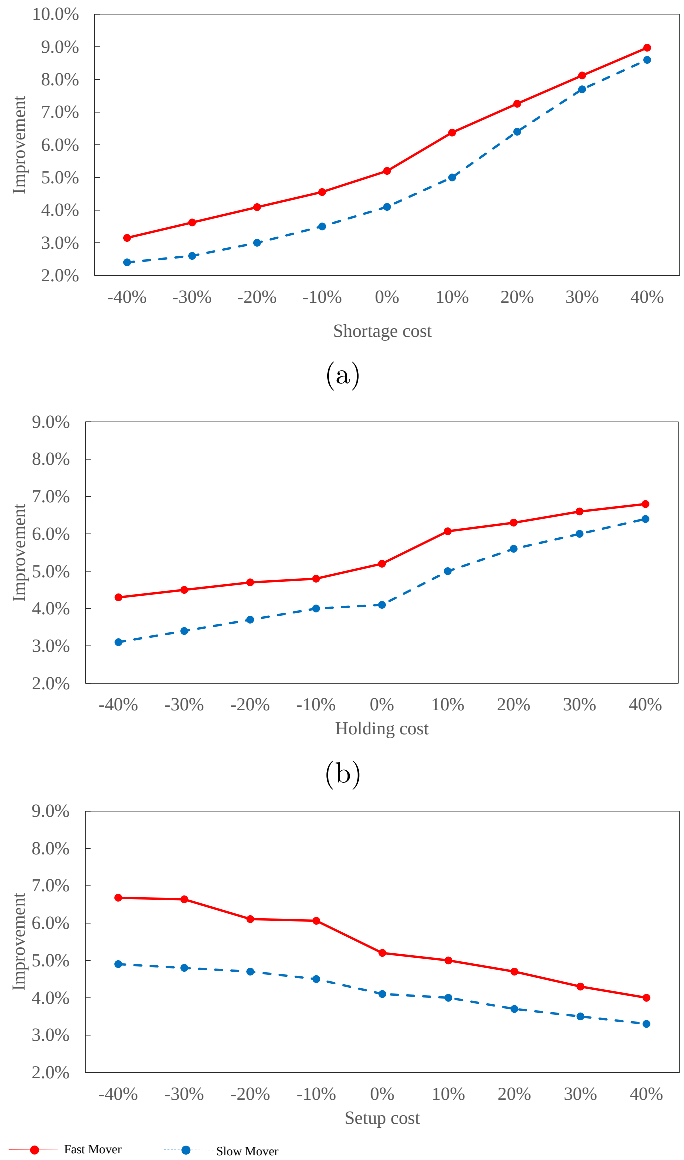
Figure 3.5 shows the sensitivity analysis for the shortage, holding, and setup costs, indicating the benefits of the proposed approach against the EF approach. According to the results, the proposed approach yields lower total costs, thus leading to significant improvement, concerning both fast and slow movers. For the fast movers, the improvement goes up by 9.1%, with the increase of shortage costs by 40%. The slow movers also show a significant improvement, although slightly smaller when compared to the fast movers, which reaches up to 8.6% as the shortage costs increases by 40%. This refinement also influences the solution, mainly when the shortage leads to significant costs (e.g., shortage costs dominate purchasing costs (Sawik, 2013)). The proposed solution approach also leads to significant improvement when the holding costs increase, although the improvement is not as substantial as the improvement when the shortage costs increase. By contrast, the decrease of setup costs indicates an increase which is moderately small, particularly for the slow movers. For these items, the improvement increases no more than 1% within the decrease of setup costs by 40%. Nevertheless, and in general terms, our proposed approach outperforms the EF approach and discloses the superiority as the extent to which a disruption mitigation strategy can be implemented.

According to the experiments, the computational time reaches up to 45.7 minutes of CPU time for the entire S-O iterations. The best solution can be found within 400 generations (see Figure 3.A.1). Making a strategic decision (such as supplier selection) within this time frame is quite reasonable. In practice, this activity takes considerably more time, particularly due to the several stages dedicated to the selection process.

3.6 Managerial Insights

3.6.1 Added Value of Modeling Imperfect Quality and TL Transportation

Imperfect quality and TL transportation are essential issues in supplier selection and inventory management, since they have a major impact on material and logistics costs, respectively. Even though it is a problem faced by most enterprises, inputs related to imperfect quality and TL transportation might not be considered when



(c)

Figure 3.5: AME improvement over EF according to different parameters' configurations: (a) shortage, (b) holding, (c) setup costs

determining inventory decisions. Practitioners need to understand how they influence costs reduction, especially costs associated with strategic items.

In order to perform this analysis, we create a set of experiments, including two different configurations. The first only considers TL transportation (disregarding imperfect quality). In this case, the order quantity is determined according to the conventional EOQ by omitting suppliers' imperfect rates (k_j). The second only considers imperfect quality (disregarding TL Transportation). According to this configuration, order quantity is determined without incorporating vehicle capacity (u_j). In other words, it no longer holds the procedure exhibited in Algorithm 1.

Finally, these two settings are compared against the full case incorporating both parameters (k_j and u_j).

Figure 3.6 shows the total cost resulting from the full case and the two configurations (TL transportation-based and imperfect quality-based problem). In the imperfect quality-based problem, total cost increases 2% and 4% when compared to the full case, for the fast and slow movers, respectively. The total costs increase at a higher pace concerning the TL transportation-based problem, reaching 5% and 9%, for the fast and slow movers, respectively. Our analysis clearly shows that neglecting suppliers' imperfect quality and vehicle capacity can result in sub-optimal supplier selection.

(a) Fast mover

(b) Slow mover

Figure 3.6: Total cost of the problem settings

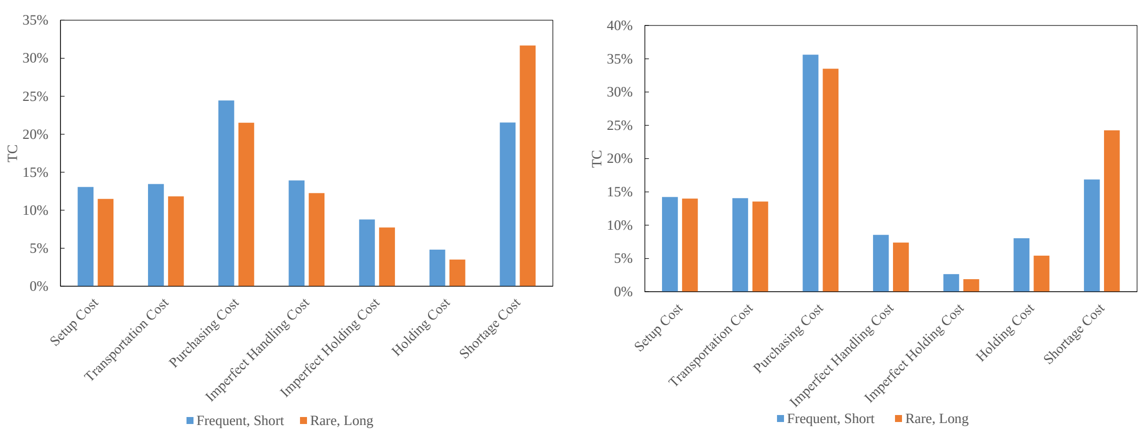
3.6.2 Impact of Disruptions

In this section, we discuss the impact of disruptions on the total costs. For the subsequent analysis, disruptions are configured with respect to the frequency and length. They can either be frequent and short or rare and long. The experiments with the fast and slow movers are performed according to specific disruption settings. Table 3 shows the disruptions' characteristics we resorted to while carrying out the experiments. Recall that θ_j stands for the disruptions' frequency, and v_j for the length.

Table 3.4: Disruption settings

Disruptions	Occurrence
Frequent, short (base case)	θ_j = U(1, 7)
	v_j = U(0.5, 2)
Rare, long	θ_j = U(40, 50)
	v_j = U(5, 10)

Naturally, different disruptions characteristics pose different effects on the total costs. According to the analysis, the differences in costs are statistically significant for some components (i.e., inventory holding and shortage costs) and not statistically significant for other components. However, there are always higher total costs incurred due to rare, long disruptions. It indicates that the impact of disruption can propagate from time period to time period (Hosseini, Ivanov et al., 2020), as the supply yield is lower (higher shortages) (V. Gupta and Ivanov, 2020). More specifically, the impact of rare, long disruptions can rise from 2% up to 12% of the total costs, particularly when compared to the scenario of frequent, short disruptions. In our inventory system, new orders can only be placed in case there is no in-transit orders, thus the disruptions forcefully block new replenishments. In addition, the imperfect items can not be used to substitute perfect items as they serve different markets. However, for product substitutions, a two-part tariff contract and a modified revenue sharing contract can be used to enhance profitability under disruptions (V. Gupta and Ivanov, 2020). Figure 3.7 represents the impact of disruptions on several costs-related components.



(a) Fast mover (b) Slow mover

Figure 3.7: The impact of disruptions on the total costs (TC)

Purchasing and shortage costs represent a considerable part of the total system costs. These significant shortages, more extensive when disruptive events occur, indicate that strategic items have a considerable impact on profit and operations, as discussed in previous studies (Caniëls and Gelderman, 2005).

The effectiveness of disruption mitigation strategies depends on the disruption characteristics. A mitigation strategy, such as the inventory control applied in our model, reduces the disruptions' impact more significantly when they are frequent and short duration, thus leading to less shortages. However, this is not enough to mitigate the impact of infrequent and longer disruptions. It is also essential to implement a proactive strategy integration, such as capacity buffers or backup facilities. In fact, specific strategic items can be sensitive to the perishability and obsolescence (e.g., highly corrosive products). Proactive strategies may not enhance the supply resilience of these items (Hosseini, Morshedlou et al., 2019). A disruption mitigation strategy at the scale of viability needs to be considered to avoid supply chain and market collapses (Ivanov and Dolgui, 2020), and therefore compensate the resilience-associated costs.

3.6.3 Impact of Supplier-related Parameters

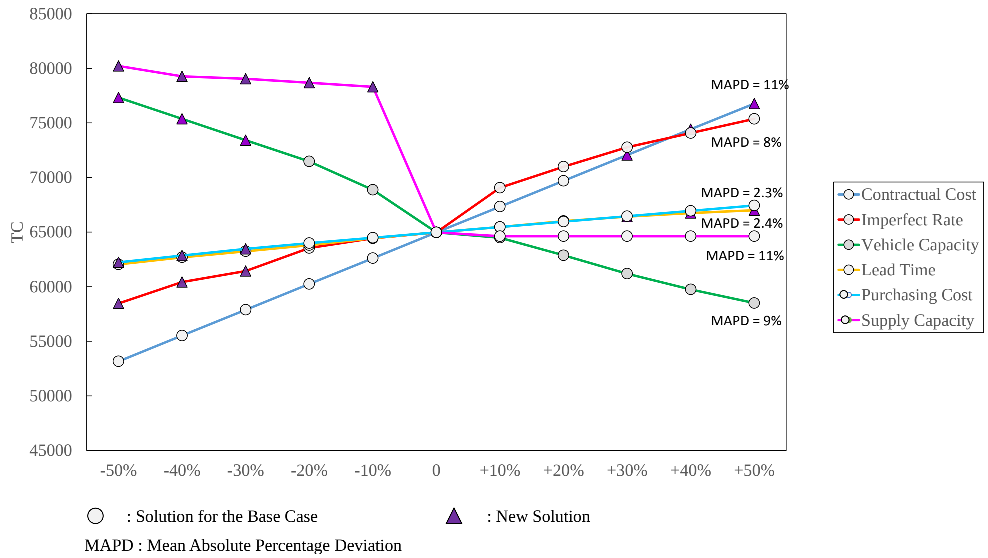
Besides disruptions, other supplier-related characteristics can substantially impact their selection, including contractual costs, vehicle capacity, imperfect rate, lead time, supply capacity, and purchasing costs. We perform a sensitivity analysis on these parameters, for both fast and slow movers, incrementing or reducing them in steps of 10%. The result of the sensitivity are included in Figure 3.8 indicating the impact of each parameter on the total costs and decisions.

The sensitivity analysis in our study draws important managerial and practical implications. It implies that the criteria importance (weight) for selecting suppliers depends on the characteristics of the items. Derived analysis should provide practitioners with an idea of the relative proper weight they should give to the different criteria; as it plays an important role in representing relative contribution at the optimal decisions (Choo et al., 1999). The results indicate that supplier selection criteria for fast movers are prioritized first based on supply capacity or contractual costs, followed by vehicle capacity or imperfect rate, and lead time or unit purchasing costs. However, this criteria priority does not hold for slow movers. For slow movers, the criteria priority is first based on supply capacity, followed by contractual costs, imperfect rate or unit purchasing costs, vehicle capacity, and lead time.

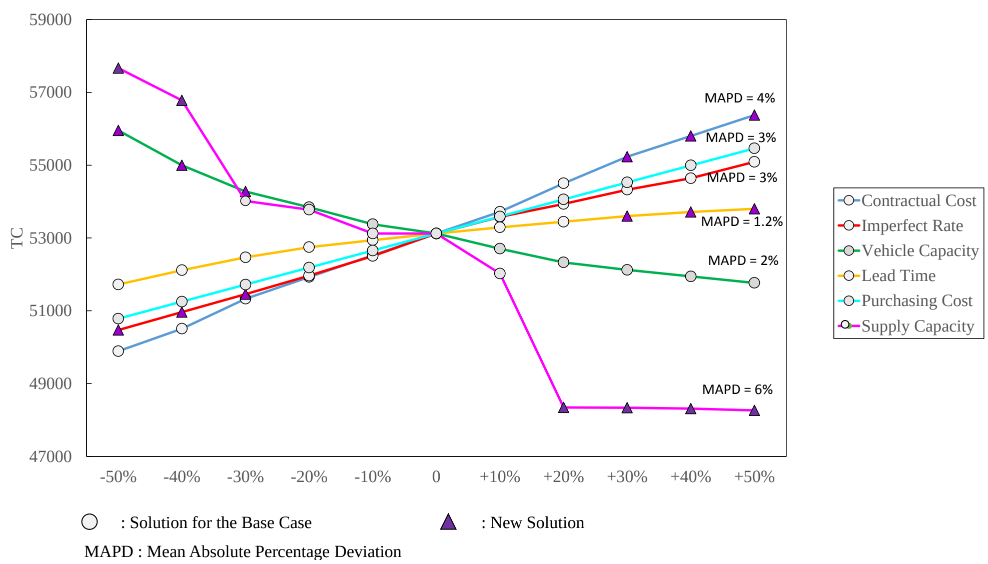
Although the criteria priority is different, supply capacity and contractual costs should have a high relative weight both for slow and fast movers due to its significant impact on total costs and decisions. As most practitioners are more likely to be concerned with unit prices when searching for the best suppliers, improving supply performance may not be easily achieved without a proper supply base. Therefore, determining the number of suppliers for optimizing the supply base depends on the supplier's supply capacity and is the foremost thing that procurement managers should be aware. Nevertheless, a buyer should always include compensation for supply base reduction in practice when cooperating with high-performing suppliers, which can be high for strategic items, as reported by the past study (Talluri et al., 2010).

3.7 Conclusion

The main issues related to finding adequate deals for material supply, generally involve quality and delivery. Material supply might include imperfect items, and order delivery might be delayed due to a disruptive event occurred at the suppliers facilities. Procurement managers might give specific instructions on how to handle imperfect items, such as separating perfect and imperfect items and store them in different warehouses. As a result, the holding costs for perfect and imperfect items might be different. The strategic initiative, such as appropriate suppliers selection, can help reducing the number of imperfect items. In addition, disruption



(a) Fast mover



(b) Slow mover

Figure 3.8: Sensitivity for supplier-related parameters

management strategy through multi-sourcing and inventory management can help mitigating the risks associated with supply, such as delivery delays, by improving the replenishment. Considering TL transportation, which has been applied in general practices and imperfect quality with specific holding costs, this study proposes a model for the integration of supplier selection and inventory management under disruptions.

We develop a simulation-optimization approach to address the problem mentioned before. Analytical model enhancement is used to accommodate the disruptions, which impact on the replenishment and order arrival as the deliveries are delayed, through enhancing reorder point based on the refined lead time. This approach focuses on the implementation of a reactive strategy to address disruptions during the proactive stage of a supply chain. It also provides comprehensive decision-making, by encouraging proper supplier selection while simultaneously determining order allocation and inventory decisions. The demand uncertainty and disruptions are incorporated in the simulation, in order to estimate the total costs of the solutions. The proposed approach can help refining the lead time in inventory management, as well as in supplier selection, particularly when shortages are costly. In other words, mitigating the risk of supply disruptions by considering the disrupted lead time in order to improve the reorder point contributes not only to a better inventory performance, but also to more selective suppliers. Nevertheless, this reactive strategy is more beneficial to protect against disruptions and reduce their impact, namely when the disruptions are frequent and short.

Based on the analysis, supply capacity, contractual costs, imperfect rate, vehicle capacity, purchasing costs, and lead time are found to be the significant factors influencing supplier selection for strategic items. However, the criteria importance should be given a different priority depending on the importance of purchasing (i.e., fast-moving and slow-moving items). Supply capacity and contractual costs are the key elements to the supplier selection process. Moreover, when contractual costs influence the system costs, the variability in supply capacity is crucial to the trade-off. Procurement managers should also focus on the vehicle capacity when selecting suppliers for fast-moving items. Furthermore, in the presence of supply disruptions, procurement managers should pay more attention to the suppliers whose imperfect rate is relatively low, in order to safeguard the more significant shortage concerning slow-moving items. In addition, the interaction of these parameters is also considered important. More specifically, there is a trade-off among the criteria that highly depends on its weight or importance.

The results of this study are subject to a limitation where the worst-case scenarios are implemented. More specifically, the entire suppliers are assumed to face disruptions (no additional order quantities are split to other suppliers during disruptions). However, in practical terms, managers can still take advantage of the multi-sourcing strategy if one of their suppliers faces disruption. Future work can be extended in several ways, including implementing other disruption mitigation strategies, such as backup sourcing, and incorporating other disruption risk factors, such as the increase of purchasing prices and the change of suppliers' capacity.

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Appendix

3.A Convergence of solution

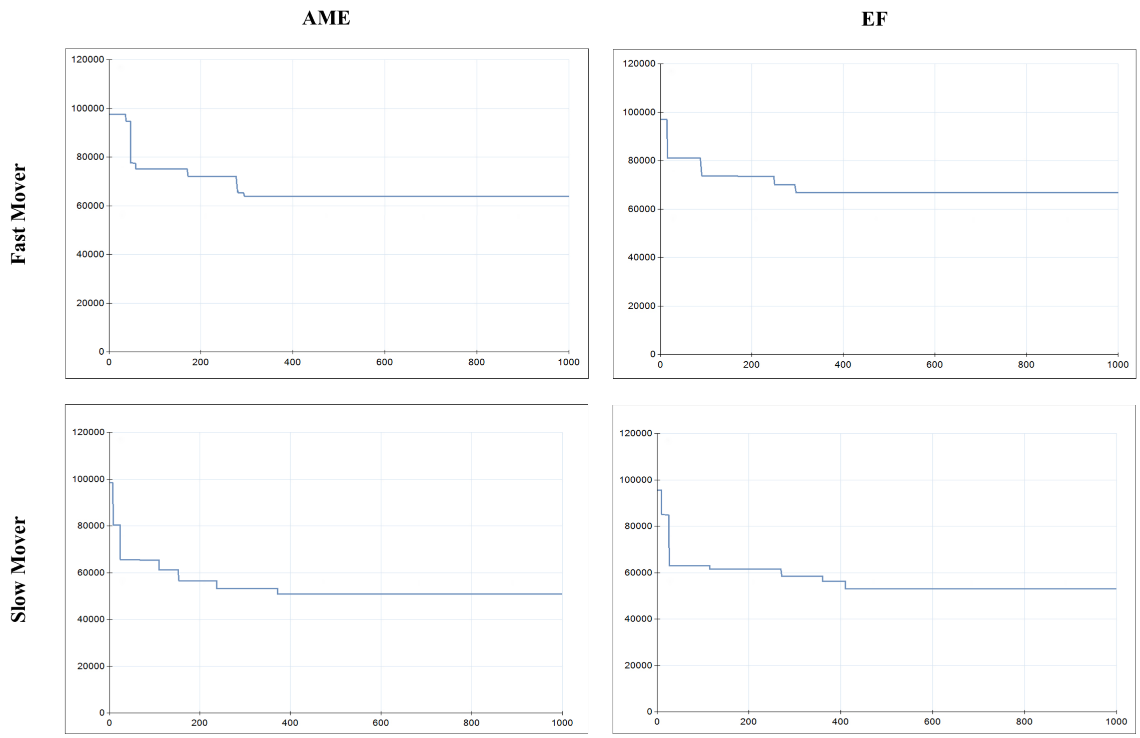
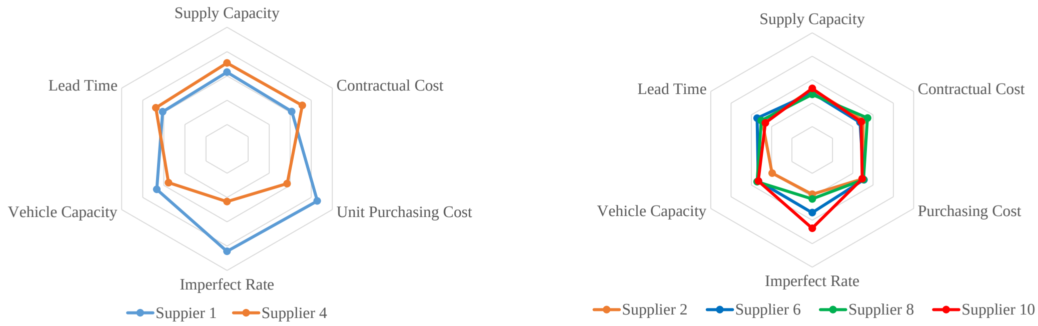


Figure 3.A.1: The convergence of solution performed by GA

3.B Impact of supplier-related parameters

Regarding the imperfect rate, although its increase leads to a significant change in the total costs, it does not result in any change to the supplier selection. On the other hand,when this parameter decreases, the supplier selection is affected. For both fast and slow movers, a new solution is found when the imperfect rate decreases by 30%. Compared to the base-case solution, supplier 1 is preferred to supplier 4, since its higher imperfect rate becomes less important, and its advantage in other parameters (vehicle capacity, lead time, and contractual costs) increases significantly. For slow movers, supplier 6 is a better choice than supplier 2, since it benefits from other parameters (vehicle capacity, supply capacity, and contractual costs). Figure 3.B.1 shows the characteristics of the selected suppliers.

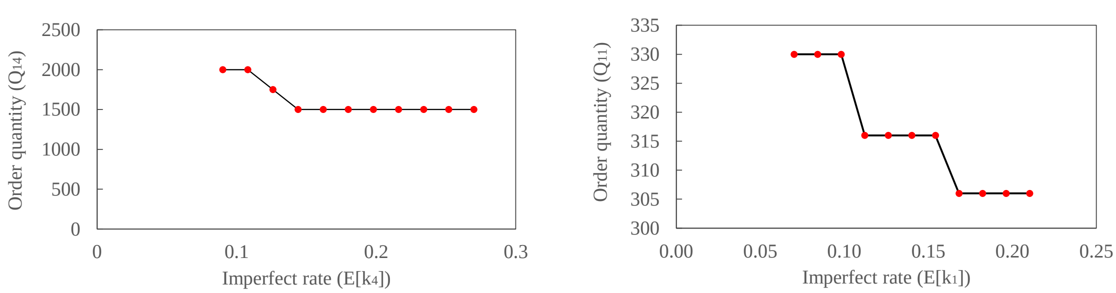


(a) Fast mover (b) Slow mover

Figure 3.B.1: Characteristics of selected suppliers

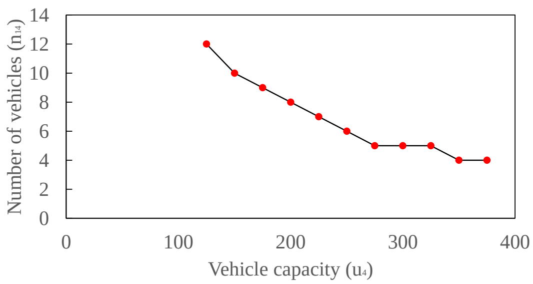
Contrary to the imperfect rate, vehicle capacity reflects a more significant influence on the total costs and supplier selection decisions, particularly when it decreases. When it decreases by 30 %, both for the fast and slow movers, it affects supplier selection decisions. Here, the base case solution is not desirable. Consequently, one of the initial suppliers should be replaced with another supplier whose vehicle capacity is larger.

Furthermore, the imperfect rate and vehicle capacity also influence the inventory decisions, particularly the order quantity. Compared to the classical inventory management, according to which the quality of the all items is assumed to be perfect, in this case, the compensation for the order quantity relies on the perfect and imperfect items' holding costs. On the other hand, incorporating imperfect rate (k_j) yields smaller order quantities (see Figure 3.B.2). The order quantity also relies on vehicle capacity, besides imperfect rate, since a TL policy is considered in this problem. As a result, the order quantity is constant at some points, instead of incremental. Beside, minimizing the transportation costs relies on the optimal number of vehicles (n_{ij}), as a function of $\lceil Q_{ij}/u_j \rceil$. As a result, optimizing order quantity (Q_{ij}) can be found within a minimum (n_{ij}) and maximum ($n_{ij}+1$) number of vehicles. We found that optimal order quantities under TL in our case satisfy the condition $Q'_{ij} \geq (n_{ij}+1)u_j$. Figure 3.B.3 shows the impact of vehicle capacity on the number of vehicles.

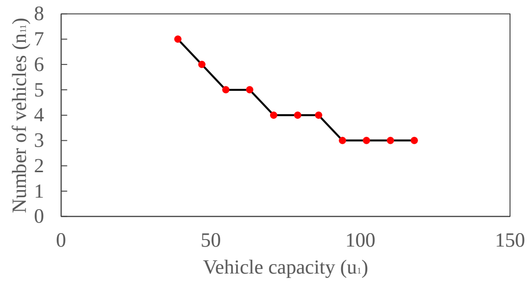


(a) Fast mover (b) Slow mover

Figure 3.B.2: Impact of imperfect rate on the order quantity (suppliers 1 and 4)



(a) Fast mover



(b) Slow mover

Figure 3.B.3: Impact of vehicle capacity on the number of vehicles (suppliers 1 and 4)

The change in unit purchasing costs does not significantly affect the total costs of the fast movers indicating a relatively small MAPD. However, supplier selection decisions are influenced by the decrease of 30% in the unit purchasing costs. By contrast, this parameter can significantly affect the total costs for expensive items, such as slow movers.

Compared to the other parameters, suppliers' lead time has a moderate impact on the total costs. We found that lead time is more significantly influential to the fast movers rather than the slow movers, and susceptible mainly when lead time is low. Lead time also has an impact on the supplier selection decisions. A new solution is found when the lead time increases by 30%. Considering the base case solution, supplier 4 is not considered a better alternative when compared to supplier 1, although its lead time is relatively low. In turn, and concerning the slow movers, supplier 8 is no longer desirable, and it ought to replaced by supplier 10.

Chapter 4

Comprehensive Supplier Selection under Uncertainty

Hybrid MCDM and Simulation-Optimization for Strategic Supplier Selection

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Abstract Supplier selection for strategic items requires a thorough framework dealing with the qualitative and quantitative aspects of a company's competitive priorities. To address these aspects, this study proposes a model with a multi-sourcing, taking into account multi-criteria, incorporating uncertainty of decision-makers' judgment and supplier-buyer parameters, and integrating with inventory management. We develop a novel two-phase solution approach based on integrated multi-criteria decision-making (MCDM) and multi-objective simulation-optimization (S-O). MCDM methods, including fuzzy AHP and interval fuzzy TOPSIS, are applied to calculate suppliers' scores, incorporating qualitative decision makers' judgment. S-O then combines the (quantitative) cost-related criteria and considers supply disruptions and uncertain supplier-buyer parameters. By running this approach on data generated based on previous studies, we evaluate the impact of decision makers' weight and objectives weight, which are considered to play an important role in supplier selection.

Keywords: Supplier selection, inventory management , multi-criteria decision-making, simulation-optimization, supply disruptions

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4.1 Introduction

Sourcing strategic items can have a significant impact on a company's profit and should therefore be undertaken from the right suppliers, with the right price and quantity, and at the right time. Selecting the right supplier relies on several processes, such as identification of criteria (Aissaoui et al., 2007; de'Boer et al., 2001), which are typically conflicting (Weber et al., 2000). A set of various criteria composed of qualitative and quantitative should be considered when evaluating suppliers (related to the main competitive priorities i.e., price, quality, delivery, flexibility, relationship, and service) (Yadav and Sharma, 2016).

Furthermore, the complexity of supply and rapid change of the global market have compelled companies to focus on risk mitigation. Mitigating risk is crucial for strategic items since the impact can be tremendous to the entire supply chain's operations. Some of the potential supply risks might come from suppliers due to delivery failures, quality problems, discontinuity of supply, or disruptions (Zsidisin, 2003). To create supply chain resilience, supplier selection processes have to be redesigned. For instance, the adoption of risk-related selection criteria (Awasthi et al., 2018; Igoulalene et al., 2015; Rajesh and Ravi, 2015) and multi-sourcing (Haleh and Hamidi, 2011), as well as the integration of inventory management (Firouz et al., 2017; Keskin et al., 2010; Saputro et al., 2020) can be important levers for risk mitigation in supplier selection.

In practice, evaluating suppliers under multiple criteria is typically performed based on decision-makers' judgment (DMs). This can lead to vague judgment when the exact values of the evaluated alternatives are not available. In this uncertain decision environment, DMs' opinions or judgments need to be perceived realistically to avoid potentially misleading decision-making. It requires transforming linguistic variables into uncertain numerical values (i.e, fuzzy or interval) (Haeri and Rezaei, 2019).

Several studies have attempted to tackle supplier selection problems under multi-criteria evaluation. Most of these studies have applied multi-criteria decision-making (MCDM) approaches, including analytical hierarchy process (AHP), analytic network process (ANP), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Chai et al., 2013). Although these methods can handle various criteria, unfortunately, a standalone MCDM method cannot properly evaluate the implications of multi-sourcing. Therefore, several studies have employed a two-phase solution approach, starting with MCDM and then optimizing order allocation of multiple suppliers (Ayhan and Kilic, 2015; Gören, 2018; Hamdan and Cheaitou, 2017; Kilic and Yalcin, 2020; Singh, 2014). Still, these studies do not accurately consider risk factors in terms of delivery delay, imperfect quality, and disruptions, and integration of mitigation strategies via inventory management.

Our study has therefore a twofold contribution. First, we propose a comprehensive model by considering both qualitative and quantitative criteria to include risk factors and applying their mitigation strategy (with multi-sourcing and inventory management). The proposed model also addresses the inherent uncertainty to accommodate more realistic DMs' judgment. Second, we develop a novel two-phase solution approach using hybrid MCDM and simulation-optimization to solve the proposed model. Two MCDM methods, namely fuzzy AHP and interval TOPSIS are employed to incorporate DMs' uncertainty in perceiving their opinion when determining the criteria weight and evaluating suppliers, respectively. In addition, the simulation-optimization method can handle uncertain supplier-related parameters (quantitative criteria) and consider disruptions.

paper content The remainder of this paper is organized as follows. Section 2 presents a brief review of relevant literature on supplier selection studies, employing a two-phase solution approach. The problem's context and model formulation are defined in Section 3. Section 4 describes the proposed solution approach, including MCDM and simulation-optimization. In Section 5, an example is given to illustrate the application of the proposed solution approach. In addition, we provide sensitivity analysis on objectives and DMs weights.

4.2 Literature Review

Studies on supplier selection have grown rapidly in the supply chain management literature. It becomes a critical concern for companies when the selection is focused on purchases that have a strategic role and impact on profitability and operations (strategic items). The problems are diverse in terms of selection criteria, sourcing strategy, decision scope, and decision environment.

Among all these problems, multi-sourcing and multi-criteria are particularly challenging and critical for strategic items in order to mitigate risk of supply and contribute profitability. Recent literature has focused on these problems (e.g., Ayhan and Kilic (2015), Cheraghalipour and Farsad (2018), Gören (2018), Hamdan and Cheaitou (2017), Kilic and Yalcin (2020) and Singh (2014)). The respective studies integrated supplier selection with order allocation, subject to uncertainty of DMs' judgment.

The aforementioned studies have proposed a two-phase solution approach dealing with multi-sourcing and incorporating qualitative and quantitative criteria, as well as DMs' judgment uncertainty for a comprehensive decision-making process. Typically, supplier evaluation with respect to the criteria is performed in the first phase of the solution approach to obtain a suppliers' score. In the second phase, final decisions regarding supplier selection and order allocation are determined, considering the suppliers' score.

The two phases are generally approached with MCDM and optimization, respectively. Singh (2014) tackled supplier selection problem using fuzzy TOPSIS and mixed-integer linear programming (MILP). Ayhan and Kilic (2015) proposed an integrated approach using fuzzy AHP to determine criteria weight and MILP to determine supplier selection and order allocation. Hamdan and Cheaitou (2017) applied integrated AHP, fuzzy TOPSIS, and mathematical programming to solve supplier selection and order allocation with a multi-objective model. In the first phase, AHP and fuzzy TOPSIS were used to determine criteria weight and supplier score, respectively. Cheraghalipour and Farsad (2018) focused on integrated supplier selection considering disruption risk. However, they did not consider the impact of disruptions, nor uncertainty was included in the model. The best-worst method was employed to determine the criteria weight and calculate the suppliers' score. The final decisions were determined via revised multi-choice goal programming. Gören (2018) introduced integrated fuzzy decision making trial and evaluation laboratory (DEMATEL), Taguchi loss function, and mathematical programming. Criteria weight and supplier score were respectively calculated using fuzzy DEMATEL and Taguchi loss function. However, suppliers' performance based on a percentage value can be difficult to be perceived and estimated by DMs for intangible criteria using Taguchi loss function. Kilic and Yalcin (2020) integrated intuitionistic fuzzy TOPSIS with fuzzy goal programming to tackle supplier selection in uncertain environment.

Table 4.2.1 summarizes the main features of these studies, including decision scope, objectives, and various sources of uncertainty. Some of those studies have addressed the aforementioned aspects, but with some limitations. The solution approach proposed by the studies depicts evaluation redundancy with respect to price or cost addressed in both phases (e.g., Cheraghalipour and Farsad (2018), Gören (2018) and Hamdan and Cheaitou (2017)). Our study's main contribution is to present a comprehensive multi-objective model by incorporating uncertainty of DMs' judgment and supplier-buyer parameters and integrating the decision scope with order allocation and inventory management. We also focus on risk mitigation by considering some risk factors (e.g., disruptions, imperfect quality, and delivery delay) and extensively take advantage of inventory management as a mitigation strategy. Besides, our study also contributes to a novel two-phase solution approach, using MCDM and S-O. More specifically, we proposed fuzzy AHP and interval TOPSIS to deal with qualitative criteria and supplier evaluation under uncertain DMs' judgment. For the final decision-making, S-O is used to optimize the decisions under multi-objectives. Also, it explicitly addresses uncertain supplier-buyer parameters or other quantitative criteria with discrete-event simulation and incorporates the disruptions information to improve the decisions. Therefore, this problem formulation is distinctive from the previous studies, as some criteria that were typically considered qualitative and more abstract are here quantified and simulated.

Simulation is indeed a flexible modeling paradigm, which, combined with optimization (S-O), allows to approach a wide variety of complex systems in uncertain environments (Wang and Shi, 2013), including production planning, transport planning, inventory management, production-distribution planning, and supply chain design (Bang and Kim, 2010). Metaheuristics are most commonly used to address these complex problems, as optimality is frequently unattainable. Combining metaheuristics with simulation can be done in different procedures depending on the simulation purpose and hierarchical structures (Figueira and Almada-Lobo, 2014). Simulation can be used to evaluate the performance of various solutions, refine or extend parameters so that a given analytical model can be enhanced, or generate solutions (Figueira and Almada-Lobo, 2014). Our case is the second, as the analytical model that allows to avoid an excessive number of simulations, and hence save computational time.

Table 4.2.1: Problem features of supplier selection

Study	Sourcing Strategy	Integration	Objective	Criteria	Uncertainty	Approach
Singh (2014)	M-S	OA	Single	Quantitative	DMs judgment	MCDM, Optimization
Ayhan & Kilic (2015)	M-S	OA	Single	Qualitative, Quantitative	DMs judgment	MCDM, Optimization
Cheaitou & Hamdan (2017)	M-S	OA	Multi	Qualitative, Quantitative	DMs judgment	MCDM, Optimization
Goren (2018)	M-S	OA	Multi	Qualitative, Quantitative	DMs judgment	MCDM, Optimization
Cheraghalipour et al. (2018)	M-S	OA	Multi	Qualitative, Quantitative	-	MCDM, Optimization
Kilic & Yalcin (2020)	M-S	OA	Multi	Qualitative, Quantitative	DMs judgment	MCDM, Optimization
This study	M-S	OA, I	Multi	Qualitative, Quantitative	DMs judgment & Supplier-buyer parameters	MCDM, Simulation-Optimization

4.3 Model Development

We study supplier selection integrated with inventory management for a single item and single-period based on a multi-sourcing strategy. We extend the model by incorporating imperfect quality, disruptions, and vehicle capacity. Suppliers are selected by considering multi-criteria classified into two objective functions, namely, maximizing a total value of purchasing (TVP) and minimizing total costs (TC).

We consider a network consisting of m suppliers ($j \in J = (1, ..., m)$) and one buyer that has n manufacturing plants ($i \in I = (1, ..., n)$) in different locations. The demand of each plant i, which follows a normal distribution, is met through the material supply from one or more suppliers j that are selected ($X_j = 1$), with certain amounts (Y_{ij}). The full notation of parameters and decision variables is shown in Table 4.3.1.

In order to manage inventory, a (Q, R) policy is applied by placing an order with a fixed quantity (Q), as soon as the inventory level drops to or below a reorder point (R). Order quantity (Q_{ij}) and reorder point (R_{ij}) have a specific amount since the order allocation of each plant is specific for each selected supplier (Y_{ij}), the so-called inventory compartmentalization.

We also consider supply disruptions and their related risk to the entire supply network, such as delivery delays. When deliveries are delayed due to disruptions, the actual observed lead time and corresponding lead time demand will be higher than the stated lead time. It is critical to mitigate their impact by avoiding more

Table 4.3.1: Input parameters and decision variables

Notation	Description
Indices	
i	: index for plant, $i = 1, 2, \ldots, n$
j	: index for supplier , $j = 1, , \ldots, m$
Parameters	
$E[D_i]$	: Expected annual demand of plant i
a_i	: External failure costs per unit for imperfect items of plant i
o_i	: Setup costs of plant i
h_i	: Holding costs per unit for perfect items of plant i
h_i'	: Holding costs per unit for imperfect items of plant i
s_i	: Shortage costs per unit and per time of plant i
f_j	: Fixed annual contractual costs of supplier j
c_j	: Purchasing costs per unit of supplier j
k_j	: Rate of imperfect quality for supplier j
b_j	: Annual supply capacity of supplier j
u_j	: Capacity of a TL vehicle for supplier j
θ_j	: Disruption frequency rate for supplier j
v_j	: Disruption length for supplier j
$E[LTD_{ij}]$	: Expected lead time demand between plant i and supplier j
$\eta[LTD_{ij}, R_{ij}]$	: Standardized loss function between plant i and supplier j
p_{ij}	: Fixed transportation costs per replenishment from supplier j to plant i
r_{ij}	: Transportation costs per mile and per replenishment from supplier j to plant i
d_{ij}	: Distance between plant i and supplier j
l_{ij}	: Lead time between plant i and supplier j
Decision variables	
X_j	: 1, if supplier j is selected; 0, otherwise
SS_j	: Score of supplier j, which refers to a closeness coefficient CC_k
Y_{ij}	: Purchase amount allocated by plant i to supplier j
Q_{ij}	: Order quantity of plant i to supplier j
R_{ij}	: Reorder point of plant i to supplier j

stock outs through proper inventory management. Thus, we determine the reorder points (R_{ij}) by incorporating an adjusted lead time (l_{ij}') that takes those disruptions into consideration. This is done through refinements undertaken by the proposed solution approach detailed in Section 4.4.2.2.

4.3.1 Total Value of Purchasing

The total value of purchasing (TVP) is the consideration in supplier selection of the maximization of the firm's long-term value. Rather than focusing on pure monetary-based values, TVP focuses on the advantage resulting from every unit purchase allocated to the selected suppliers. Since sourcing experiences from every unit purchase can affect a firm's willingness to buy and perceptions toward suppliers, TVP relies on purchase quantity (Y_{ij}). In this context, TVP is perceived based on the non-monetary criteria, which contribute to an intangible value of advantages. This includes service (C1), relationship (C2), and flexibility (C3).

In order to calculate TVP, we assess suppliers based on the aforementioned criteria. The supplier's performance score (SS_j) is a function of those criteria ($SS_j = CC_k = f(C1_k, C2_k, C3_k)$, where $k = j$) which is derived through multi-criteria decision-making approaches. Finally, TVP is maximized by using the following expression.

$$\text{Max } Z1 \text{ (TVP)} = \sum_{i}^{n}\sum_{j}^{m} SS_j Y_{ij} \tag{4.1}$$

4.3.2 Total Costs

Total costs (TC) are considered monetary-based values, which consist of contractual and purchasing costs (Eq. 4.2), inventory costs (Eq. 4.3-a, 4.3-b), transportation costs (Eqs. 4.4), external failure, and imperfect holding costs (Eq. 4.5).

$$\text{Min } Z2 \text{ (TC)} = \sum_{j=1}^{m} f_j X_j + \sum_{i=1}^{n}\sum_{j=1}^{m} c_j Y_{ij} \tag{4.2}$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{o_i Y_{ij}}{Q_{ij}(1-E[k_j])} + \sum_{i=1}^{n}\sum_{j=1}^{m} h_i \left(\frac{Q_{ij}(1-E[k_j])}{2} + R_{ij} - E[LTD_{ij}] \right) \tag{4.3-a}$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{m} s_i \eta(LTD_{ij}, R_{ij}) \frac{Y_{ij}}{Q_{ij}(1-E[k_j])} \tag{4.3-b}$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{(p_{ij} + r_{ij} d_{ij}) \lceil \frac{Q_{ij}}{u_j} \rceil Y_{ij}}{Q_{ij}(1-E[k_j])} \tag{4.4}$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{m} a_i Y_{ij} E[k_j] + \sum_{i=1}^{n}\sum_{j=1}^{m} h_i' Q_{ij} E[k_j] \tag{4.5}$$

Fixed contractual costs (f_j) incur once a contract is awarded to the selected supplier. Moreover, each plant has to pay variable purchasing costs (c_j) for the order allocated to a supplier.

Some other costs also have to be paid throughout the supply, including inventory and transportation. More specifically, transportation cost for each delivery is charged according to vehicle capacity (u_j), considering mileage (r_{ij}) and fixed costs (p_{ij}). Total inventory costs are calculated according to setup costs (o_i) and inventory carrying costs (h_i). Additionally, shortage costs incur if stock outs occur at plant ($s_i, i \in I$). Due to their different distance and location, a lead time for each pair of supply (supplier-plant) (l_{ij}) is specific. $\eta(.,.)$ in (eq. **??**) represents the standard loss function.

The average annual transportation costs (eq. **??**) are calculated according to the vehicle capacity u_j. The costs per vehicle are measured based on the fixed vehicle charge (p_{ij}) and mileage costs (r_{ij}). In (eq. **??**), d_j represents the distance between suppliers and plants, which is measured according to Euclidean measure associated with suppliers' coordinates d_j and plants' coordinates d_i.

We also consider a quality risk by incorporating suppliers' quality variability and its associated costs. In this regard, the incoming material from a supplier includes a specific rate of imperfect quality (k_j). As a result, plants have to spend a specific holding cost (h'_i) for these imperfect items. Additionally, external failure costs (a_i) incurs due to liability or complaints by customers acquiring imperfect items. The expected imperfect rate ($E[k_j]$) is taken into account as a function of the inventory, transportation, and external failure costs. $E[k_j]$ is computed according to a particular distribution; more specifically, it is perceived as uniformly distributed.

4.3.3 Constraints

The main constraints regard capacity and demand fulfillment.

Constraint (4.6) ensures that the order allocated to the selected suppliers Y_{ij} must satisfy the demand in each plant $E[D_i]$.

$$\sum_{j=1}^{m} Y_{ij} = E[D_i], \quad \forall i \in I \tag{4.6}$$

Due to the suppliers' capacity constraint, the order allocation Y_{ij} should not exceed their capacity b_j.

$$\sum_{i=1}^{n} Y_{ij} \leq b_j X_j, \quad \forall j \in J \tag{4.7}$$

Finally, constraint (4.8) represents non-negativity and binary decision variables.

$$Y_{ij} \geq 0, \quad Q_{ij} \geq 0, \quad X_j = 0 \; or \; 1, \quad \forall i \in I, \ \forall j \in J \tag{4.8}$$

4.4 Proposed Approach

In order to solve the problem, a two-phase solution approach is developed integrating MCDM and simulation-optimization. In the first phase, we focus on suppliers' evaluation based on the qualitative criteria. We determine the criteria weight using fuzzy AHP and calculate the supplier score using interval TOPSIS. Then, supplier scores are included into the objective function depicted in Eq. (1), to be optimized at the second phase.

After multi-criteria evaluation, the second phase focuses on solving the multi-objective mathematical model defined in Section 3, integrating supplier selection, order allocation, and inventory management. Simulation-optimization is developed to solve this phase. The two-phase solution approach in this study is illustrated in Figure 4.4.1.

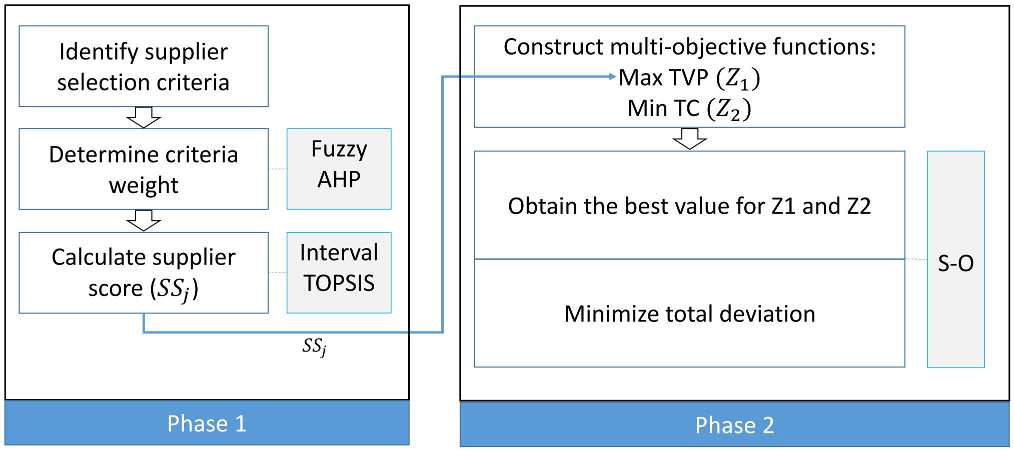


Figure 4.4.1: Two-phase solution approach: MCDM and simulation-optimization

4.4.1 MCDM

First, criteria weights are determined using fuzzy AHP. Criteria are given different importance by DMs which is perceived using linguistic variables. The linguistic variables are then transformed into its respective triangular fuzzy numbers (TFN) for each Saaty's scale shown in Table 4.4.1.

Second, alternatives are evaluated by DMs under each criterion using linguistic variables. Then, DMs judgment is transformed into an interval value shown in Table 4.4.2. To calculate the score of alternatives, interval TOPSIS is employed.

Table 4.4.1: Linguistic variables for the importance of the criterion

Linguistic variables	**Saaty's Scale**	**TFN**
Equally important	1	1, 1, 1
Weakly or slighty more important	2	1, 2, 3
Moderately more important	3	2, 3, 4
Moderately plus more important	4	3, 4, 5
Strongly more important	5	4, 5, 6
Strongly plus more important	6	5, 6, 7
Strongly very more important	7	6, 7, 8
Very, very strongly more important	8	7, 8, 9
Absolutely more important	9	8, 9, 9

Table 4.4.2: Linguistic variables for the rating of the alternative

Linguistic Variable	**Interval Number**
Very Poor (VP)	0, 1
Poor (P)	1, 3
Medium Poor (MP)	3, 4
Fair (F)	4, 5
Medium Good (MG)	5, 6
Good (G)	6, 9
Very Good (VG)	9, 10

4.4.1.1 Fuzzy AHP

AHP has been widely used for a wide area of decision-making problems due to its advantages: i) it can be used not only to assess relative criteria weights but also to assess the performance of alternatives through pairwise comparisons, ii) it can handle both tangible and intangible attributes, iii) it is suitable for a hierarchical structure of criteria (fundamental components and inter-dependencies) (Zardari et al., 2015).

To deal with qualitative, imprecise information or even incomplete-structures decision problems, fuzzy set theory is employed as a modeling tool for complex systems that can be controlled by humans but are not easy to define exactly. It provides a sensible way to represent vague, ambiguous, and imprecise input of knowledge. Decision makers are usually more confident to perceive interval judgments rather fixed value (crisp) judgments when their opinions can be explicit due to fuzzy nature of evaluation process.

According to fuzzy set theory, crisp values are transformed into fuzzy numbers. A triangular fuzzy number (TFN) is widely used as fuzzy numbers. It involves lower, middle, and upper values.

Definition 4.1. A fuzzy number M on $R \in (-\infty, +\infty)$ is defined to be a fuzzy triangular number if its membership function $\mu_m : R \rightarrow [0, 1]$ is equal to:

$$\mu_m(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l}, & \text{if } x \in [l, m] \\ \frac{x}{m-u} - \frac{l}{m-l}, & \text{if } x \in [m, u] \\ 0, & \text{otherwise} \end{cases} \tag{4.9}$$

In Eq. (4.9) l and u stand for the lower and upper value of fuzzy number M, respectively, and m represents the middle value, where $l \leq m \leq u$. A TFN, expressed in Eq. (4.9), is denoted as (l, m, u). The basic operations of TFNs are defined in Table 4.4.3.

The deficiency of AHP to deal with the imprecision and subjectiveness in the pairwise comparison process has been improved in fuzzy AHP (Demirel et al., 2008). In this study, fuzzy AHP proposed by Chang (1996) is adopted to determine criteria weight.

Table 4.4.3: The algebraic operations of fuzzy numbers

Fuzzy Operation	**Fuzzy Formula**	**Calculation Operation**
Addition	$\tilde{a_1} \oplus \tilde{a_1}$	$(l_1 + 1_2, m_1 + m_2, u_1 + u_2)$
Subtraction	$\tilde{a_1} \ominus \tilde{a_1}$	$(l_1 + u_2, m_1 + m_2, u_1 + l_2)$
Multiplication	$\tilde{a_1} \otimes \tilde{a_1}$	$(l_1.1_2, m_1.m_2, u_1.u_2)$
Division	$\frac{1}{\tilde{a_1}}$	$(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1})$

Let $C = \{C_1, C_2, ..., C_n\}(j = 1, 2, ..., n)$ represent the element of supplier selection criteria. Thus, criteria weight is determined according to the following steps:

Step 1. Construct pairwise comparison matrix for each pair of criteria according to the linguistic variables shown in Table 4.4.1.

Step 2. Transform the matrix into triangular fuzzy numbers (TFN) (c.f. Table 4.4.1) denoted by $M_{gi}^{j}, j \in N$.

Step 3. Calculate the value of fuzzy synthetic with respect to the i^{th} criterion using

$$S_i = \sum_{j=1}^{n} M_{gi}^{j} \otimes \left[\sum_{i=1}^{m} \sum_{j=1}^{n} M_{gi}^{j}\right]^{-1} \tag{4.10}$$

where

$$\sum_{j=1}^{n} M_{gi}^{j} = \left(\sum_{i=1}^{m} l_i, \sum_{i=1}^{m} m_i, \sum_{i=1}^{m} u_i\right)$$

$$\left[\sum_{i=1}^{m} \sum_{j=1}^{n} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{m} u_i, \sum_{i=1}^{m} m_i, \sum_{i=1}^{m} l_i}\right)$$

Step 4. Determine the degree of possibility of $M_{2(l,m,u)} \geq M_{1(l,m,u)}$ using

$$V(M_2 \geq M_1) = \sup_{y \geq x} \lfloor min(\mu_{M_1}(x), \mu_{M_2}(y)) \rfloor \tag{4.11}$$

$$V(M_2 \geq M_1) = hgt(\mu_{M_1} \cap \mu_{M_2}) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases}$$

Step 5. Define a convex fuzzy number as

$$V(F \geq F_1, F_2, ..., F_k) = min\ V(F \geq F_i),\ \ i = 1, 2, ..., k \tag{4.12}$$

$$V(F_i) = min\ V(F_i \geq F_k) = W_i',\ k = 1, 2, ..., n \text{ and } k \neq i$$

Step 6. Determine the criteria weight vector using

$$W' = (W_1', W_2', ..., W_n')^T \tag{4.13}$$

Step 7. After normalization, obtain the priority weights as

$$W = (W_1, W_w, ..., W_n)^T \tag{4.14}$$

where W is a crisp number

4.4.1.2 Interval TOPSIS

TOPSIS is a method based on the concept that the ranking of alternatives is based on the shortest distance from the positive-ideal solution (PIS) and the farthest distance from the negative-ideal solution (NIS) (Hwang and Yoon, 1981). The wide application of TOPSIS in decision-making problems comes from its advantages, including: i) a sound logic that represents the rationale of DM's choice; ii) a scalar value that accounts for both the best and worst alternatives simultaneously; iii) it is not restrained by the human capacity for information processing since DM's evaluation is based on cardinal absolute measurement instead of pairwise comparison; iv) a sensible computation process that can be programmed easily into a spreadsheet (Shih et al., 2007). By using pairwise comparison, consistent judgment becomes very difficult to make when evaluating typically more than seven alternatives since the number of pairwise comparisons increases rapidly with the number of criteria or alternatives ($n(n-1)/2$) (Shih et al., 2007). Therefore, we can use TOPSIS to evaluate a number of suppliers.

Decision-makers would be more comfortable to perceive their opinion into interval measurement when confronting with uncertainty or lack of certain information. According to Jahanshahloo et al. (2009), we adapt interval TOPSIS in this study. Each step of the procedure is explained in the following.

Let $A = \{A_1, A_2, ..., A_m\}(i = 1, 2, ..., m)$ be a discrete set of m feasible alternatives, $C = \{C_1, C_2, ..., C_n\}(j = 1, 2, ..., n)$ be a finite set of attributes, and $DM = \{DM_1, DM_2, ..., DM_l\}(k = 1, 2, ..., l)$ be a group of DMs.

Step 1. For each DM, evaluate each alternative with respect to n attributes using linguistic variables, as shown in Table 4.4.2, whose value is an interval ($x_{ij} \in [\, x_{ij}^{(l)},\ x_{ij}^{(u)}]\,$).

Step 2. For each DM, construct decision matrix which denotes by

$$X_k = ([\, x_{ij}^{(l)}, x_{ij}^{(u)}]\,)_{m\text{x}n} \tag{4.15}$$

$$
= \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array}
\begin{array}{c}
\begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\
\begin{pmatrix}
[\,x_{11}^{k(l)},\; x_{11}^{k(u)}] & [\,x_{12}^{k(l)},\; x_{12}^{k(u)}] & \ldots & [\,x_{1n}^{k(l)},\; x_{1n}^{k(u)}] \\
[\,x_{21}^{k(l)},\; x_{21}^{k(u)}] & [\,x_{22}^{k(l)},\; x_{22}^{k(u)}] & \ldots & [\,x_{2n}^{k(l)},\; x_{2n}^{k(u)}] \\
\vdots & \vdots & \vdots & \vdots \\
[\,x_{m1}^{k(l)},\; x_{m1}^{k(u)}] & [\,x_{m2}^{k(l)},\; x_{m2}^{k(u)}] & \ldots & [\,x_{mn}^{k(l)},\; x_{mn}^{k(u)}]
\end{pmatrix}
\end{array}
$$

Step 3. The weight of k^{th} DMs ($k \in L$) is denoted by vector $\lambda = (\lambda_1, \lambda_2, ..., \lambda_l)^T$, such that $\lambda_k \geq 0$, $\sum_{k=1}^{l} = 1$. Given the DMs weight, aggregate the decision matrices into a collective matrix G.

$$
G = \sum_{k=1}^{l} \lambda_k G_k = ([\,g_{ij}^{(l)},\; g_{ij}^{(u)}]\,)_{mxn} \tag{4.16}
$$

Step 4. Calculate the normalized decision matrix R

$$
R_k = ([\,r_{ij}^{(l)},\; r_{ij}^{(u)}]\,)_{mxn} \tag{4.17}
$$

$$
= \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array}
\begin{array}{c}
\begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\
\begin{pmatrix}
[\,r_{11}^{(l)},\; r_{11}^{(u)}] & [\,r_{12}^{(l)},\; r_{12}^{(u)}] & \ldots & [\,r_{1n}^{(l)},\; r_{1n}^{(u)}] \\
[\,r_{21}^{(l)},\; r_{21}^{(u)}] & [\,r_{22}^{(l)},\; r_{22}^{(u)}] & \ldots & [\,r_{2n}^{(l)},\; r_{2n}^{(u)}] \\
\vdots & \vdots & \vdots & \vdots \\
[\,r_{m1}^{(l)},\; r_{m1}^{(u)}] & [\,r_{m2}^{(l)},\; r_{m2}^{(u)}] & \ldots & [\,r_{mn}^{(l)},\; r_{mn}^{(u)}]
\end{pmatrix}
\end{array}
$$

We can further transform the aggregated decision matrix $([\,g_{ij}^{(l)},\; g_{ij}^{(u)}]\,)_{mxn}$ into normalized decision matrix $([\,r_{ij}^{(l)},\; r_{ij}^{(u)}]\,)_{mxn}$ using the following formula

$$
r_{ij}^{(l)} = \frac{g_{ij}^{(l)}}{\sqrt{\sum_{i=1}^{m} (g_{ij}^{(l)})^2 + (g_{ij}^{(u)})^2}}, \;\; \forall i \in M,\; j \in N \tag{4.18}
$$

$$
r_{ij}^{(u)} = \frac{g_{ij}^{(u)}}{\sqrt{\sum_{i=1}^{m} (g_{ij}^{(l)})^2 + (g_{ij}^{(u)})^2}}, \;\; \forall i \in M,\; j \in N \tag{4.19}
$$

Step 5. Calculate weighted normalized decision matrix R considering the different importance of each attribute as decision matrix V.

$$
V = ([\,v_{ij}^{(l)},\; v_{ij}^{(u)}]\,)_{mxn} = ([\,w_j r_{ij}^{(l)},\; w_j r_{ij}^{(u)}]\,)_{mxn} \tag{4.20}
$$

$$
= \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array}
\begin{array}{c}
\begin{array}{cccc} \quad C_1 \quad & \quad C_2 \quad & \ldots & \quad C_n \quad \end{array} \\
\begin{pmatrix}
[\,v_{11}^{(l)},\ v_{11}^{(u)}] & [\,v_{12}^{(l)},\ v_{12}^{(u)}] & \ldots & [\,v_{1n}^{(l)},\ v_{1n}^{(u)}] \\
[\,v_{21}^{(l)},\ v_{21}^{(u)}] & [\,v_{22}^{(l)},\ v_{22}^{(u)}] & \ldots & [\,v_{2n}^{(l)},\ v_{2n}^{(u)}] \\
\vdots & \vdots & \vdots & \vdots \\
[\,v_{m1}^{(l)},\ v_{m1}^{(u)}] & [\,v_{m2}^{(l)},\ v_{m2}^{(u)}] & \ldots & [\,v_{mn}^{(l)},\ v_{mn}^{(u)}]
\end{pmatrix}
\end{array}
$$

where w_j is the weight of the j^{th} attribute, such that $0 \leq w_j \leq 1,$ and $\sum_{j=1}^{n} w_j = 1.$

Step 6. Find the positive ideal solution (PIS) and negative ideal solution (NIS), using the following step:

- PIS

  Determine the best value of alternative A_k based on the criteria, such as maximum for benefit criteria and minimum for cost criteria. Accordingly, $A_k^{+(u)}$ can be defined as follows:

$$
A_k^{+(u)} = \{(v_1^{+(u)},\ v_2^{+(u)}, ...,\ v_n^{+(u)})\} = \{(max\ v_{ij}^{(u)} \mid i \in O),\ (min\ v_{ij}^{(l)} \mid i \in I)\} \tag{4.21}
$$

  where O is associated with benefit criteria and I with cost criteria.

  Determine the worst value for alternative A_k based on the criteria, such as minimum for benefit criteria and maximum for cost criteria. $A_k^{+(l)}$ can be found using the following form:

$$
A_k^{+(l)} = \{(v_1^{+(l)},\ v_2^{+(l)}, ...,\ v_n^{+(l)})\} \tag{4.22}
$$

$$
= \{(max_{j \neq i}\ \{v_{ij}^{(u)},\ v_{ij}^{(l)} \mid i \in O),\ (min_{j \neq i}\ \{v_{ij}^{(u)},\ v_{ij}^{(l)} \mid i \in I)\}
$$

- NIS

$$
A_k^{-(u)} = \{(v_1^{-(u)},\ v_2^{-(u)}, ...,\ v_n^{-(u)})\} \tag{4.23}
$$

$$
= \{(min_{j \neq i}\ \{v_{ij}^{(u)},\ v_{ij}^{(l)} \mid i \in O),\ (max_{j \neq i}\ \{v_{ij}^{(u)},\ v_{ij}^{(l)} \mid i \in I)\}
$$

$$
A_k^{-(l)} = \{(v_1^{-(l)},\ v_2^{-(l)}, ...,\ v_n^{-(l)})\} \tag{4.24}
$$

$$
= \{(min\ v_{ij}^{(l)} \mid i \in O),\ (max\ v_{ij}^{(u)} \mid i \in I)\}
$$

Step 7. Calculate the distance of each individual decision A_k from the PIS $(d_k^{+(l)},\ d_k^{+(u)})$ and NIS $(d_k^{-(l)},\ d_k^{-(u)})$ using the n-dimensional Euclidean distance.

$$d_k^{+(u)} = \sqrt{\sum_{i \in I}(v_i^{+(u)} - d_{ik}^{(u)})^2 + \sum_{i \in O}(v_i^{+(u)} - d_{ik}^{(l)})^2} \tag{4.25}$$

$$d_k^{+(l)} = \sqrt{\sum_{i \in I}(v_i^{+(l)} - d_{ik}^{(l)})^2 + \sum_{i \in O}(v_i^{+(l)} - d_{ik}^{(u)})^2}$$

$$d_k^{-(u)} = \sqrt{\sum_{i \in I}(v_i^{-(l)} - d_{ik}^{(l)})^2 + \sum_{i \in O}(v_i^{-(l)} - d_{ik}^{(u)})^2}$$

$$d_k^{-(l)} = \sqrt{\sum_{i \in I}(v_i^{-(u)} - d_{ik}^{(l)})^2 + \sum_{i \in O}(v_i^{-(u)} - d_{ik}^{(u)})^2}$$

Step 8. Calculate closeness coefficient ($CC_k^{(l)},\ CC_k^{(u)}$), using following formula

$$CC_k^{(l)} = \frac{d_k^{-(l)}}{d_k^{-(u)} + d_k^{+(u)}} \tag{4.26}$$

$$CC_k^{(u)} = \frac{d_k^{-(u)}}{d_k^{-(u)} + d_k^{+(u)}}$$

Step 9. Rank the best alternative. We adopt Sengupta's approach in the following.

Calculate the mid-point $m(CC_k)$ and half width of the interval closeness coefficient $w(CC_k)$ using

$$m(CC_k) = \frac{1}{2}(CC_k^{(l)} + CC_k^{(u)}) \tag{4.27}$$

$$w(CC_k) = \frac{1}{2}(CC_k^{(u)} - CC_k^{(l)}) \tag{4.28}$$

According to the acceptability function, compare two alternatives a and b as follows:

$$\mathcal{A}_{(<)} = \frac{m(b) - m(a)}{w(b) + w(a)} \cdot \mathcal{A}_{(<)} \tag{4.29}$$

$\mathcal{A}_{(<)}$ can be interpreted as the first interval to be inferior to the second interval. The term "inferior to" ("superior to") can be defined as "less than" ("greater than"). Decision-makers can select an alternative between two according to the value of $\mathcal{A}_{(<)}$. According to this procedure, the best choice of alternative can stand for the one with a smaller uncertain interval (the half width) if two interval numbers have the same mid-point.

4.4.2 Simulation-Optimization

4.4.2.1 Multi-Objective Approach

First, we divide the multi-objective model defined in Section 4.3 into two single-objective sub-problems. The first sub-problem is defined according to the objective function in Eq. (4.1) and constraints in Eqs. (4.6), (4.7), and (4.8). The second sub-problem comprises objective function in Eqs. (4.2) - (4.5) and subjects to the same constraints. We solve these two sub-problems separately using an S-O approach to obtain their best solutions, $Z1_{max}$ and $Z2_{min}$, respectively.

Second, distance method is used to calculate the deviation of the objective function (e) representing the distance from the ideal solution (Z^*, where $Z^* = Z_{max}$ for maximization, $Z^* = Z_{min}$ for minimization).

$$f1 = \frac{Z1_{max} - Z1}{Z1_{max}} \tag{4.30-a}$$

$$f2 = \frac{Z2 - Z2_{min}}{Z2_{min}} \tag{4.30-b}$$

Finally, we transform both objective functions into a single objective for minimizing total deviation (e) using the weighted comprehensive criterion method (WCCM) (Abdallah et al., 2021). The importance weights (α_1, α_2) is also assigned to each objective function. A single objective function is expressed as follows.

$$\text{Min } e = \alpha_1.f1 + \alpha_2.f2 \tag{4.31}$$

$s.t.$

$$Eqs.\ (4.6), (4.7), (4.8) \tag{4.32}$$

where $\alpha_1 + \alpha_2 = 1$.

4.4.2.2 Analytic Model Enhancement (AME)

We develop simulation-optimization using a genetic algorithm (GA) to search within the solution space. A simulation model provides a thorough evaluation for stochastic input parameters, considering stochastic demand, uncertain imperfect rate, and disruptions. In our proposed approach, the GA optimizes decision variables of X (supplier selection) based on the performance measure (e) formulated in Eq. (4.31).

Given the value of X, which is randomly selected, we determine order allocation (Y) according to the transportation cost given by (4.4) in the objective function, constraints (4.6) and (4.7). More specifically, we derived the solution using a transportation method. Then, the optimal order quantity from a plant to a supplier (Q_{ij}) is obtained according to inventory costs given by (4.3-a), (4.3-b), and imperfect items' holding costs (4.5).. To incorporate vehicle capacity, order quantity is determined by using a heuristic (see Saputro et al. (2020)).

The solutions containing supplier selection (X) and inventory decisions (Q, R) are then passed to the simulation incorporating demand uncertainty and disruptions for objective function evaluation (e). The optimization process is powered by simulation's feedback, which is used to refine the lead-time (L). It is used to address possible delays that result from disruptions. The analytical expression (R, Q) is then enhanced while the lead-time is refined. This simulation-optimization approach is known as an analytic model enhancement (AME). The refinement procedure begins such that, for every randomly selected X, and each replication, the lead time derived from simulation based on the mean value is sent for optimization. According to the refined lead time, the reorder point is recalculated. The performance measure (e) is returned to the optimization according to the decision variables sent to the simulation. The GA then uses this performance measure to optimize the solutions. The illustration of AME is shown in Figure 4.4.2.

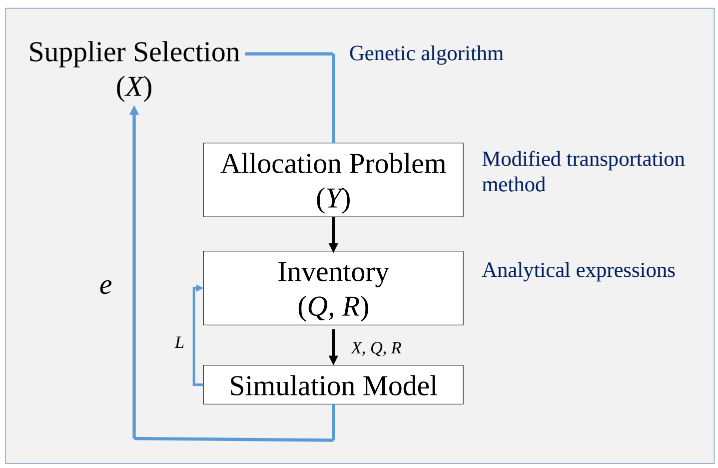


Figure 4.4.2: Simulation-optimization: Analytic model enhancement

4.5 Computational Experiments

In this study, we consider a firm that operates eight manufacturing plants located in different regions. The material supply of each manufacturing plant is sourced from two or more suppliers. There are ten candidate suppliers to be evaluated under qualitative and quantitative criteria. We use qualitative criteria and their evaluation based on the decision-makers' judgment from Yadav and Sharma (2016)'s study. Quantitative criteria and other parameters indicated in Eqs. (4.2)-(4.5), (4.6), and (4.7) are adopted from Saputro et al. (2020).These quantitative criteria will be assessed objectively in a monetary based-value. The respective quantitative and qualitative criteria are summarized in Table 4.5.1. In addition, the values of input parameters, representing fast-moving items, are indicated in Table 4.5.2.

Table 4.5.1: Quantitative and qualitative supplier selection criteria

Category	Criteria	Sub-criteria	Category	Criteria	Sub-criteria
Quantitative	Cost	Purchasing cost (c)	Qualitative	Service	Technical support
		Contractual cost (f)			Information sharing
		Transportation cost (p, r)			Warranty & claim policy
	Quality	Rate of perfect quality ($1 - k$)			Capabilities
	Delivery	Lead time (l)		Relationship	Honesty
		On-time delivery (*simulation*)			Reputation
		Vehicle capacity (u)			Trust & partnership
		Distance (d)			Ease of communication
	Technology	Supply capacity (b)		Flexibility	Product mix flexibility
	Risk	Disruptions (θ, v)			Volume flexibility
		Disruptive lead time (*simulation*)			Process flexibility
		Rate of imperfect quality (k)			Service flexibility

Table 4.5.2: Input parameters for fast movers

Parameters		Values	Units
Plant, $i \in I$			
Demand	μ_i, σ_i	: U(1000, 3000), U(150, 300)	unit/year
Setup costs	o_i	: U(500, 1000)	\$/order
Holding costs	h_i	: U(0.5, 3.0)	\$/unit/year
Shortage costs	s_i	: U(5.0, 10.0)	\$/unit/year
Imperfect items' holding costs	h'_i	: U(0.25, 1.5)	\$/unit/year
External failure costs	a_i	: U(0.2, 1)	\$/unit
Location		: [U(0, 500), U(0, 500)]	
Supplier, $j \in J$			
Supply capacity	b_j	: U(7500, 10000)	unit
Imperfect rate	k_j	: U(0.15, 0.35)	
Vehicle capacity	u_j	: U(150, 300)	unit/vehicle
Disruption frequency	θ_j	: U(1, 7)	days
Disruption length	v_j	: U(0.5, 2)	days
Contractual costs	f_j	: U(50000, 100000)	\$
Unit purchasing costs	c_j	: U(0.4, 2.0)	\$/unit
Location		: [U(0, 500), U(0, 500)]	
Plant-Supplier, $i \in I, j \in J$			
Fixed transportation costs	p_{ij}	: U(250, 500)	\$/order/vehicle
Variable transportation costs	r_{ij}	: U(0.75, 3)	\$/mile/vehicle
Lead time	l_{ij}	: $\left(\frac{U(1,2)}{60}\right) d_{ij}$	hours

4.5.1 Suppliers Assessment based on Qualitative Criteria

4.5.1.1 Determining Criteria Weight

There are 3 criteria and 12 sub-criteria associated with qualitative measures. A decision-maker assessed the criteria and sub-criteria using fuzzy pairwise comparison matrices shown in Table 4.5.3 and Table 4.5.4, respectively. Finally, the weights are calculated using Fuzzy AHP and the result is shown in Table 4.D.1.

Table 4.5.3: Fuzzy pairwise comparison matrix among qualitative criteria

Citeria	Service (C1)	Relationship (C2)	Flexibility (C3)
Service (C1)	1, 1, 1	2, 3, 4	1, 2, 3
Relationship (C2)	1/4, 1/3, 1/2	1, 1, 1	1/3, 1/2, 1
Flexibility (C3)	1/3, 1/2, 1	1, 2, 3	1, 1, 1

Table 4.5.4: Fuzzy pairwise comparison matrix among sub-criteria

Service (C1)	Technical support (SC1)	Information sharing (SC2)	Warranty and claim policy (SC3)	Capabilities (SC4)
Technical support (SC1)	1, 1, 1	2, 3, 4	1/4, 1/3, 1/2	1, 2, 3
Information sharing (SC2)	1/4, 1/3, 1/2	1, 1, 1	1/5, 1/4, 1/3	1/4, 1/3, 1/2
Warranty and claim policy (SC3)	2, 3, 4	1, 1, 1	1, 1, 1	2, 3, 4
Capabilities (SC4)	1/3, 1/2, 1	2, 3, 4	1/4, 1/3, 1/2	1, 1, 1
Relationship (C2)	**Honesty (SC5)**	**Reputation (SC6)**	**Trust & partnership (SC7)**	**Ease of communication (SC8)**
Honesty (SC5)	1, 1, 1	2, 3, 4	4, 5, 6	4, 5, 6
Reputation (SC6)	1/4, 1/3, 1/2	1, 1, 1	2, 3, 4	2, 3, 4
Trust & partnership (SC7)	1/6, 1/5, 1/4	1/4, 1/3, 1/2	1, 1, 1	1, 2, 3
Ease of communication (SC8)	1/6, 1/5, 1/4	1/4, 1/3, 1/2	1/3, 1/2, 1	1, 1, 1
Flexibility (C3)	**Product mix flexibility (SC9)**	**Volume flexibility (SC10)**	**Process flexibility (SC11)**	**Service flexibility (SC12)**
Product mix flexibility (SC9)	1, 1, 1	1/4, 1/3, 1/2	1, 2, 3	1/4, 1/3, 1/2
Volume flexibility (SC10)	2, 3, 4	1, 1, 1	3, 4, 5	1/3, 1/2, 1
Process flexibility (SC11)	1/3, 1/2, 1	1/5, 1/4, 1/3	1, 1, 1	1/4, 1/3, 1/2
Service flexibility (SC12)	2, 3, 4	1, 2, 3	2, 3, 4	1, 1, 1

Criteria with a high importance weight become a critical aspect of evaluation. According to Table 4.D.1, the DM considers warranty and claim policy as the most critical one for supplier evaluation, followed by technical support, service flexibility, and volume flexibility, respectively.

4.5.1.2 Determining Suppliers Score

In this stage, suppliers performance are evaluated under sub-criteria using linguistic variables expressed in Table 4.4.2. The decision maker judgment regarding suppliers performance is summarized in Table 4.5.5. According to this information, the DM' judgments are transformed into their respective interval numbers shown in Table 4.5.6. SSupplier score is then determined using interval TOPSIS, and sub-criteria global weights (w_j), indicated in Table 4.D.1 are used for this calculation (see Eq.

(4.20)).Finally, supplier score (SS_j) is derived based on the mid-point of the closeness coefficient ($SS_j = CC_k,$ where $k = j$), shown in Table 4.5.7.

Table 4.5.5: Supplier performance under DM's judgement

Supplier	**Sub-criteria**											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	F	MG	F	MG	MP	F	G	P	P	F	MP	MG
2	F	MP	G	F	MP	F	G	F	MP	MP	MP	MP
3	MP	MG	F	MP	MP	F	MP	F	MG	P	P	F
4	F	P	G	F	P	MG	F	MP	F	MG	P	F
5	MP	F	G	F	P	MG	F	F	P	MG	P	P
6	MP	MP	G	MG	MP	F	MP	P	P	F	P	P
7	MP	F	G	F	P	P	F	F	F	P	P	F
8	F	MP	G	G	MP	MG	MG	P	P	MP	P	MP
9	MP	P	MP	MG	P	P	MG	F	F	MP	MP	MG
10	F	MG	MP	G	P	MP	G	F	MP	P	MP	MG

Table 4.5.6: Interval values for supplier assessment

Supplier	**Sub-criteria**											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	[4, 5]	[5, 6]	[4, 5]	[5, 6]	[3, 4]	[4, 5]	[6, 9]	[1, 3]	[1, 3]	[4, 5]	[3, 4]	[5, 6]
2	[4, 5]	[3, 4]	[6, 9]	[4, 5]	[3, 4]	[4, 5]	[6, 9]	[4, 5]	[3, 4]	[3, 4]	[3, 4]	[3, 4]
3	[3, 4]	[5, 6]	[4, 5]	[3, 4]	[3, 4]	[4, 5]	[3, 4]	[4, 5]	[5, 6]	[1, 3]	[1, 3]	[4, 5]
4	[4, 5]	[1, 3]	[6, 9]	[4, 5]	[1, 3]	[5, 6]	[4, 5]	[3, 4]	[4, 5]	[5, 6]	[1, 3]	[4, 5]
5	[3, 4]	[4, 5]	[6, 9]	[4, 5]	[1, 3]	[5, 6]	[4, 5]	[4, 5]	[1, 3]	[5, 6]	[1, 3]	[1, 3]
6	[3, 4]	[3, 4]	[6, 9]	[5, 6]	[3, 4]	[4, 5]	[3, 4]	[1, 3]	[1, 3]	[4, 5]	[1, 3]	[1, 3]
7	[3, 4]	[4, 5]	[6, 9]	[4, 5]	[1, 3]	[1, 3]	[4, 5]	[4, 5]	[4, 5]	[1, 3]	[1, 3]	[4, 5]
8	[4, 5]	[3, 4]	[6, 9]	[6, 9]	[3, 4]	[5, 6]	[5, 6]	[1, 3]	[1, 3]	[3, 4]	[1, 3]	[3, 4]
9	[3, 4]	[1, 3]	[3, 4]	[5, 6]	[1, 3]	[1, 3]	[5, 6]	[4, 5]	[4, 5]	[3, 4]	[3, 4]	[5, 6]
10	[4, 5]	MG	[3, 4]	[6, 9]	[1, 3]	[3, 4]	[6, 9]	[4, 5]	[3, 4]	[1, 3]	[3, 4]	[5, 6]

According to the closeness coefficient, supplier 4 has the best qualitative evaluation since it has the highest score. This implies that its overall performance is far from the worst existing evaluation. The second and third best alternatives refer to suppliers 8 and 2, respectively. Supplier 10 represents the worst-performing alternative although its performance on six out of ten criteria is better than supplier 8. This happened mainly due to the criteria weight assigned by the DM. In this study, sub-criteria, including technical support (SC1), warranty & claim policy (SC3), volume flexibility (SC10), and service flexibility (SC12), are given a high priority. At least under one of these sub-criteria (i.e., technical support, warranty & claim policy, and volume flexibility), the performance of supplier 10 underperforms supplier 8.

Table 4.5.7: Suppliers score based on the closeness coefficient

Supplier	Closeness Coefficient (CC_k)		
	Interval	**Mid-point**	**Half-width**
1	[0.377, 0.685]	0.531	0.154
2	[0.324, 0.814]	0.569	0.245
3	[0.299, 0.532]	0.416	0.117
4	[0.420, 0.842]	0.631	0.211
5	[0.367, 0.760]	0.564	0.197
6	[0.339, 0.769]	0.554	0.215
7	[0.335, 0.757]	0.546	0.211
8	[0.330, 0.836]	0.583	0.253
9	[0.330, 0.539]	0.435	0.104
10	[0.319, 0.544]	0.397	0.112

4.5.2 Final Selection

The final decision-making for the integrated supplier selection is accomplished by solving the multi-objective model (described in Section 3) using an S-O approach considering disruptions (c.f. Section 4.2). We construct objective function $Z1$, incorporating supplier scores (SS_j) obtained from interval TOPSIS, and objective function $Z2$.

The best values are 14893 and 64972, respectively for $Z1_{max}$ and $Z2_{min}$. For $Z1_{max}$, supplier 4 and 8 are selected. While for $Z2_{min}$, selected suppliers include 4 and 6.

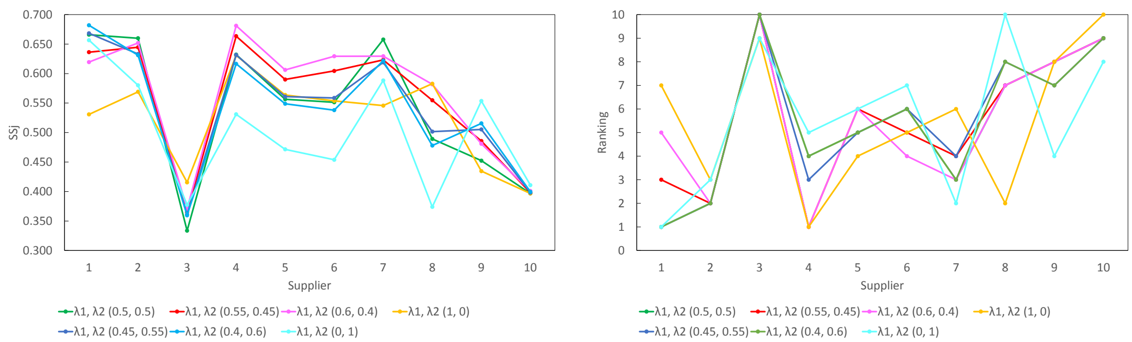
After deriving the best value of each objective, the final solution is derived by minimizing total deviation of both objectives using Eq. (4.31)and setting up $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$. The best solution was found with a deviation of 0.073 (see Figure 4.A.1). Selected suppliers include 4 and 6. This indicates that $Z1_{max}$ is compromised to achieve the trade-off.

4.5.3 Sensitivity Analysis

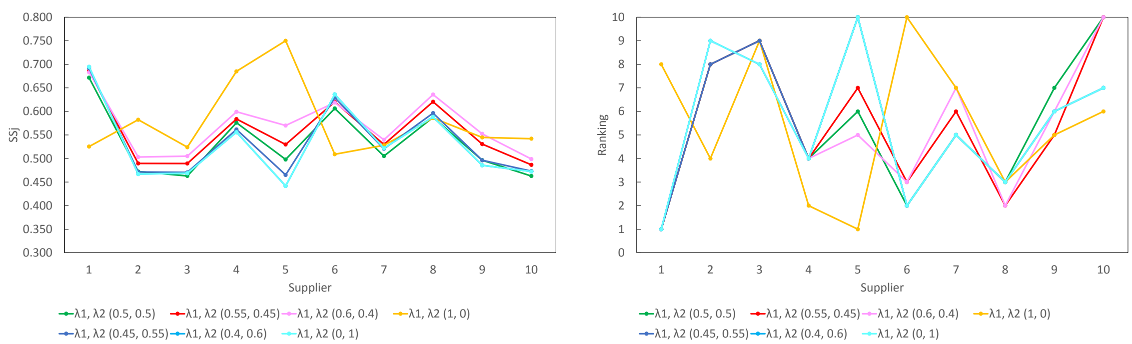
This analysis aims to investigate the impact of DM weight and objective weight. In order to arrive at more general conclusions, we created an additional scenario by using different values of input parameters, as seen in Table 4.E.1. The values represent slow- moving items adopted from Saputro et al. (2020). Additionally, DMs' judgments for suppliers are provided in Appendix 4.C. The analysis is respectively presented in Section 4.5.3.1 and 4.5.3.2, emphasizing some key aspects.

4.5.3.1 Impact of Decision Maker Weight

We investigate the impact of DMs weight (λ_k) on the suppliers score (SS_j) and their associated ranking. Thus, we consider an additional DM, namely DM_1 and DM_2. To perform this analysis, we just focus on the first phase of the solution approach for problems 1 and 2fast and slow movers. For each pair of λ_1 and λ_2, we set up the weight varying from 0.4 up to 0.6, and $\lambda_1 + \lambda_2 = 1$. The results of the sensitivity analysis are shown in Figure 4.5.1.



(a) Fast movers



(b) Slow movers

Figure 4.5.1: Impact of DMs weight (λ_k) on the suppliers score (SS_j) and ranking

Figure 4.5.1 indicates that the opinions of each DM toward suppliers performance can differ. Variation of both suppliers score and ranking is considerable for each DM ($\lambda_1 = 1$ *or* $\lambda_2 = 1$). For fast movers, DM1 and DM2 make contrast assessment for suppliers 1, 7, 8, and 9. While for slow movers, assessment of suppliers 1, 2, 5, 6, and 9 contrast between DM1 and DM2. Therefore, to accommodate the different opinions, weight needs to be assigned to each DM so that consensus can be achieved.

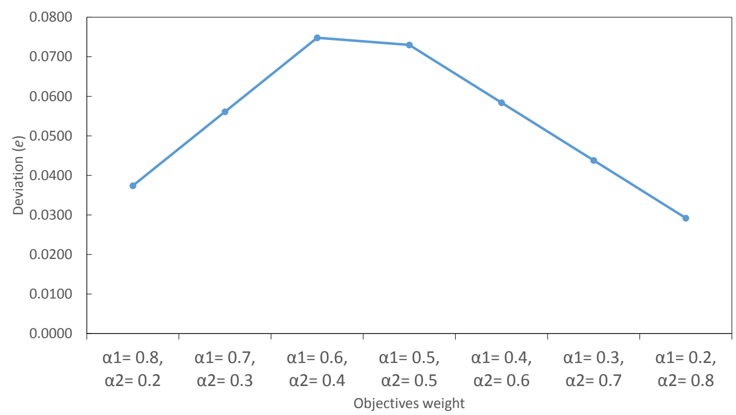
The result of the sensitivity shows that the impact of λ_k on supplier score and ranking is quite evident. It improves satisfaction degree of consensus for each DM. According to each scenario of DMs weight, small variation can be achieved when $\lambda_1 = 0.45$ and $\lambda_2 = 0.55$ for fast movers, and $\lambda_1 = 0.4$ and $\lambda_2 = 0.6$ for slow movers. Tabel 4.5.8 shows the mean variation of suppliers' score according to different scenarios of λ_1 and λ_2 against a single $\lambda(\lambda_1 = 1$ *or* $\lambda_2 = 1)$.

Table 4.5.8: Variation of supplier score according to different scenarios of (λ_k)

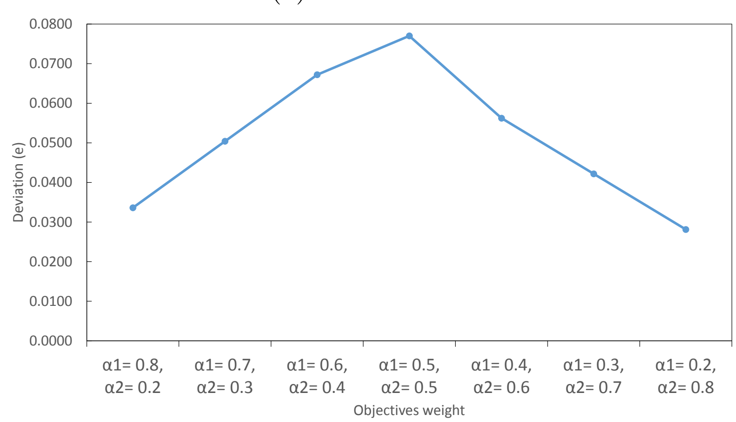
Problem	Scenarios				
	λ_1, λ_2 (0.6, 0.4)	λ_1, λ_2 (0.55, 0.45)	λ_1, λ_2 (0.5, 0.5)	λ_1, λ_2 (0.45, 0.55)	λ_1, λ_2 (0.4, 0.6)
Fast movers	0.2920	0.2658	0.2534	0.2230	0.2234
Slow movers	0.2128	0.1953	0.1894	0.1784	0.1728

4.5.3.2 Impact of Objective Weight

Analysis regarding the impact of objective weight (α_k) is further performed for each problem. The objective weight varies between 0.2 and 0.8 for each pair of α_1 and α_2. The results of this sensitivity analysis are shown in Figure 4.5.2.



(a) Fast movers



(b) Slow movers

Figure 4.5.2: Impact of objective weight (α_k) on the deviation (e)

Both scenarios indicate that the trade-off between objective functions $Z1$ and $Z2$ decreases when weights are more unbalanced. In those cases, the total deviation of the objectives tends to decrease. By contrast, total deviation increases when the weight of both objectives is nearly the same. Thus, it is not easy to achieve a high yield without compromising another objective.

Furthermore, our analysis indicates that the best trade-off is achieved when $Z2$ is given a priority, resulting in lower deviation compared to other scenarios. The total deviation on average decreases by 22% and 16%, respectively for fast and slow movers, for $\alpha_2 > 0.5$. In other words, minimizing total costs can be considered more important than maximizing the total value of purchasing when selecting suppliers. This is aligned with the insight pointed by the case study explored by Gören (2018).

4.6 Conclusion

Due to high-profit impact and supply complexity, this study addresses a supplier selection problem incorporating criteria holistically under uncertainty and disruptions risk mitigation. A novel two-phase solution approach is proposed to solve the model with multi-objective. Fuzzy AHP and interval TOPSIS are respectively used to perceive imprecise DMs' judgment in determining weight and assessing suppliers under qualitative criteria. The final decision-making process is performed using S-O based on analytic model enhancement (AME). AME provides a better decision for supplier selection and inventory management since the lead time is refined according to the disruption information. In other words, this solution approach is useful to deal with disruption risk mitigation.

Our analysis draws important implications for decision-makers in supplier selection. Selection criteria should be well incorporated for both qualitative and quantitative. Evaluating suppliers under quantitative criteria should be objectively performed as it can be measured based on a monetary-based value. This monetary measure should be the focus for purchases comprising high-profit impact. The quantitative criteria become a critical aspect since it refers to a firm's core performance (e.g., quality, delivery, and cost). Also, it is associated with risk factors (i.e., disruptions, imperfect quality, delivery delay), which becomes a critical issue for the purchases whose supply complexity is high such as strategic items. It becomes relevant since it also affects inventory decisions (Saputro et al., 2020).

Under uncertainty in which information regarding suppliers can be incomplete or non-obtainable, imprecise or vague judgment raises particularly for qualitative criteria. This can result in contradictory judgment among DMs. Therefore, a weight needs to be assigned to each DM to accommodate the degree of satisfaction. In practice, it is important to look at DMs' knowledge, experience, and consistency when assigning their weights.

A pre-qualification or screening process might be established in supplier selection, particularly when the number of candidates restrains human's evaluation capacity. The two-phase solution approach proposed in this study discloses a comprehensive decision-making process, which does not need pre-qualification. This also enhances the final decision-making by optimizing the decisions jointly via S-O, considering multi-objectives.

This study has limitations that might lead to interesting future research. Despite the fact that the study has addressed the risk factors (i.g., disruptions, imperfect quality, delivery delay), other risk factors in global sourcing might also exist due to political or social instability. The future study can be extended, considering this aspect to sustain resilient supplier selection in global sourcing. Furthermore, the increase of awareness on sustainability might compel firms to identify related criteria and incorporate them into supplier selection. Developing a framework for supplier evaluation under sustainability could also be an interesting future research direction.

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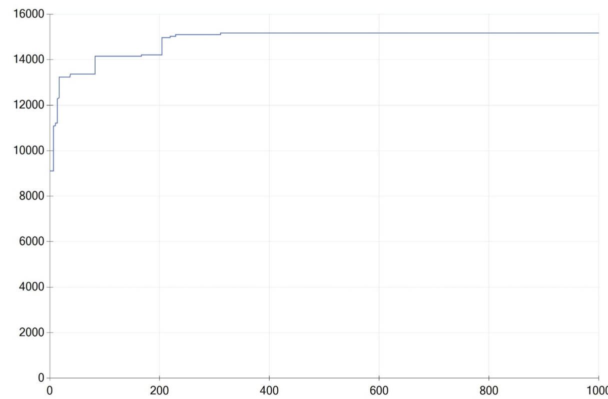
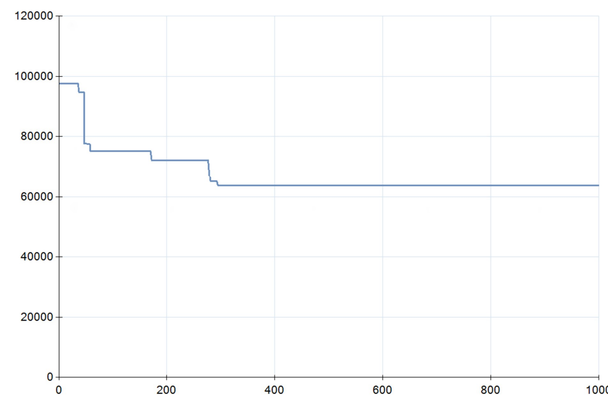
Appendix

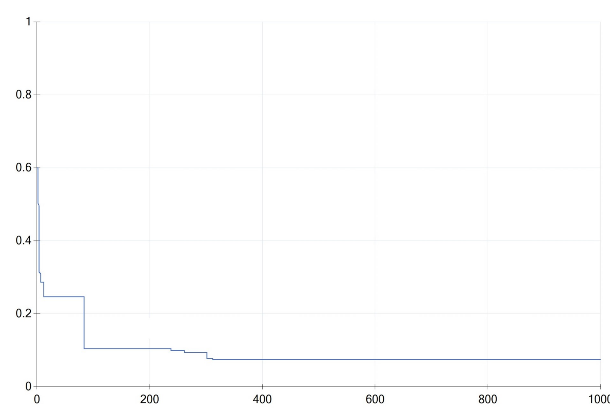
4.A Convergence of Genetic Algorithm



(a)



(b)



(c)

Figure 4.A.1: The convergence under multi-objective settings: (a) Value of purchasing ($Z1$), (b) Total costs ($Z2$), (c) Total deviation (e)

4.B Qualitative Criteria: Strategic Items Suppliers

Table 4.B.1: Qualitative criteria for supplier selection

Criteria	Description	Sub-criteria	Description
Service	The after-sales service which promotes customers satisfaction and influences customer purchasing intentions	Technical support	Commitement of a supplier to provide technical support services
		Information sharing	The willingness of a supplier to share technical information
		Warranty and claim policy	The intention of a supplier to provide warranties or agreements between the customer and the supplier for the faulty products
		Capabilities	The capability of a supplier to resolve issues or conflict
Relationship	The buyer–supplier relationship that enhances mutual motivation and results in better development of the total economy	Honesty	The attitude and responsibility of managers in professional relationship
		Reputation	The track record of Supplier indicating a cooperation experience with large enterprises
		Trust & partnership	The commitment s of a supplier to Establish mutually beneficial long-term supplier relationship
		Ease of communication	The ability of supplier in providing an effective commutations system to customers
Flexibility	The ability of a supplier to adapt to external changes while maintaining satisfactory system performance	Product mix flexibility	The ability to change the variety of products produced (customers' orders)
		Volume flexibility	The ability to respond to change in demand
		Process flexibility	The ability to adapt the production technology and its process in order to respond to the new customer product characteristics
		Service flexibility	The ability to handle the abnormal orders without compromising the existing product price

4.C Decision Makers Judgment

Table 4.C.1: DM2: Linguistic variables of supplier assessment for problem 1

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	F	MP	G	MG	MP	MG	F	F	F	MP	MP	F
2	MP	F	G	F	P	MG	F	F	F	P	P	MP
3	P	P	MP	F	P	MG	MP	MP	P	MP	P	MP
4	F	MP	MP	F	MP	MP	MG	P	MG	MG	P	F
5	F	P	P	G	P	F	G	F	P	F	MP	MG
6	P	MG	F	MG	MP	MG	MP	F	P	MP	P	MP
7	P	MG	G	MG	P	P	G	F	P	MP	P	MG
8	MP	MP	P	MG	P	MG	MP	P	MG	P	MP	MP
9	P	F	F	G	MP	F	F	P	MG	MG	MP	MG
10	MP	MP	MP	F	MP	F	MG	MP	MP	P	P	MP

Table 4.C.2: DM2: Interval values of supplier assessment for problem 1

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	[4, 5]	[3, 4]	[6, 9]	[5, 6]	[3, 4]	[5, 6]	[4, 5]	[4, 5]	[4, 5]	[3, 4]	[3, 4]	[4, 5]
2	[3, 4]	[4, 5]	[6, 9]	[4, 5]	[1, 3]	[5, 6]	[4, 5]	[4, 5]	[4, 5]	[1, 3]	[1, 3]	[3, 4]
3	[1, 3]	[1, 3]	[3, 4]	[4, 5]	[1, 3]	[5, 6]	[3, 4]	[3, 4]	[1, 3]	[3, 4]	[1, 3]	[3, 4]
4	[4, 5]	[3, 4]	[3, 4]	[4, 5]	[3, 4]	[3, 4]	[5, 6]	[1, 3]	[5, 6]	[5, 6]	[1, 3]	[4, 5]
5	[4, 5]	[1, 3]	[1, 3]	[6, 9]	[1, 3]	[4, 5]	[6, 9]	[4, 5]	[1, 3]	[4, 5]	[3, 4]	[5, 6]
6	[1, 3]	[5, 6]	[4, 5]	[5, 6]	[3, 4]	[5, 6]	[3, 4]	[4, 5]	[1, 3]	[3, 4]	[1, 3]	[3, 4]
7	[1, 3]	[5, 6]	[6, 9]	[5, 6]	[1, 3]	[1, 3]	[6, 9]	[4, 5]	[1, 3]	[3, 4]	[1, 3]	[5, 6]
8	[3, 4]	[3, 4]	[1, 3]	[5, 6]	[1, 3]	[5, 6]	[3, 4]	[1, 3]	[5, 6]	[1, 3]	[3, 4]	[3, 4]
9	[1, 3]	[4, 5]	[4, 5]	[6, 9]	[3, 4]	[4, 5]	[4, 5]	[1, 3]	[5, 6]	[5, 6]	[3, 4]	[5, 6]
10	[3, 4]	[3, 4]	[3, 4]	[4, 5]	[3, 4]	[4, 5]	[5, 6]	[3, 4]	[3, 4]	[1, 3]	[1, 3]	[3, 4]

Table 4.C.3: DM1: Linguistic variables of supplier assessment for problem 2

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	P	F	MG	G	P	P	G	F	P	MP	MP	P
2	MP	P	MP	MP	MP	P	MP	MP	MP	F	MP	F
3	MP	MP	F	MG	MP	MG	G	MP	MP	MP	P	P
4	F	MP	F	MP	MP	MG	F	MP	F	MP	MP	MG
5	MP	MP	MG	G	P	P	MG	F	F	F	MP	MG
6	MP	MG	MG	MP	MP	MP	MG	F	MG	P	MP	P
7	F	P	MG	F	MP	P	MG	P	MP	P	MP	P
8	F	P	MG	G	MP	MG	MP	F	P	MP	MP	P
9	F	MG	MG	MG	MP	P	F	F	F	P	MP	P
10	P	F	F	MG	MP	P	MG	P	P	MP	P	MP

Table 4.C.4: DM1: Interval values of supplier assessment for problem 2

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	[1, 3]	[4, 5]	[5, 6]	[6, 9]	[1, 3]	[1, 3]	[6, 9]	[4, 5]	[1, 3]	[3, 4]	[3, 4]	[1, 3]
2	[3, 4]	[1, 3]	[3, 4]	[3, 4]	[3, 4]	[1, 3]	[3, 4]	[3, 4]	[3, 4]	[4, 5]	[3, 4]	[4, 5]
3	[3, 4]	[3, 4]	[4, 5]	[5, 6]	[3, 4]	[5, 6]	[6, 9]	[3, 4]	[3, 4]	[3, 4]	[1, 3]	[1, 3]
4	[4, 5]	[3, 4]	[4, 5]	[3, 4]	[3, 4]	[5, 6]	[4, 5]	[3, 4]	[4, 5]	[3, 4]	[3, 4]	[5, 6]
5	[3, 4]	[3, 4]	[5, 6]	[6, 9]	[1, 3]	[1, 3]	[5, 6]	[4, 5]	[4, 5]	[4, 5]	[3, 4]	[5, 6]
6	[3, 4]	[5, 6]	[5, 6]	[3, 4]	[3, 4]	[3, 4]	[5, 6]	[4, 5]	[5, 6]	[1, 3]	[3, 4]	[1, 3]
7	[4, 5]	[1, 3]	[5, 6]	[4, 5]	[3, 4]	[1, 3]	[5, 6]	[1, 3]	[3, 4]	[1, 3]	[3, 4]	[1, 3]
8	[4, 5]	[1, 3]	[5, 6]	[6, 9]	[3, 4]	[5, 6]	[3, 4]	[4, 5]	[1, 3]	[3, 4]	[3, 4]	[1, 3]
9	[4, 5]	[5, 6]	[5, 6]	[5, 6]	[3, 4]	[1, 3]	[4, 5]	[4, 5]	[4, 5]	[1, 3]	[3, 4]	[1, 3]
10	[1, 3]	[4, 5]	[4, 5]	[5, 6]	[3, 4]	[1, 3]	[5, 6]	[1, 3]	[1, 3]	[3, 4]	[1, 3]	[3, 4]

Table 4.C.5: DM2: Linguistic variables of supplier assessment for problem 2

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	F	F	G	MP	MP	MP	G	F	P	MP	P	MG
2	MP	P	MP	G	MP	F	G	P	MP	MG	P	F
3	MP	MP	F	MG	P	MG	G	MP	MG	P	P	MG
4	MP	MG	F	MG	MP	MG	MP	F	MG	MG	P	F
5	F	F	P	MG	MP	P	MP	F	F	P	MP	MG
6	MP	P	G	G	P	MP	P	F	MG	P	P	F
7	F	MG	MG	MG	P	P	G	F	MP	P	MP	MP
8	F	F	F	MG	MP	MG	P	P	F	MG	MP	F
9	F	P	MP	G	MP	P	F	MP	F	MP	P	MG
10	F	MG	F	F	MP	P	F	F	F	F	MP	P

Table 4.C.6: DM2: Interval values of supplier assessment for problem 2

Supplier	Sub-criteria											
	SC1	**SC2**	**SC3**	**SC4**	**SC5**	**SC6**	**SC7**	**SC8**	**SC9**	**SC10**	**SC11**	**SC12**
1	[4, 5]	[4, 5]	[6, 9]	[3, 4]	[3, 4]	[3, 4]	[6, 9]	[4, 5]	[1, 3]	[3, 4]	[1, 3]	[5, 6]
2	[3, 4]	[1, 3]	[3, 4]	[6, 9]	[3, 4]	[4, 5]	[6, 9]	[1, 3]	[3, 4]	[5, 6]	[1, 3]	[4, 5]
3	[3, 4]	[3, 4]	[4, 5]	[5, 6]	[1, 3]	[5, 6]	[6, 9]	[3, 4]	[5, 6]	[1, 3]	[1, 3]	[5, 6]
4	[3, 4]	[5, 6]	[4, 5]	[5, 6]	[3, 4]	[5, 6]	[3, 4]	[4, 5]	[5, 6]	[5, 6]	[1, 3]	[4, 5]
5	[4, 5]	[4, 5]	[1, 3]	[5, 6]	[3, 4]	[1, 3]	[3, 4]	[4, 5]	[4, 5]	[1, 3]	[3, 4]	[5, 6]
6	[3, 4]	[1, 3]	[6, 9]	[6, 9]	[1, 3]	[3, 4]	[1, 3]	[4, 5]	[5, 6]	[1, 3]	[1, 3]	[4, 5]
7	[4, 5]	[5, 6]	[5, 6]	[5, 6]	[1, 3]	[1, 3]	[6, 9]	[4, 5]	[3, 4]	[1, 3]	[3, 4]	[3, 4]
8	[4, 5]	[4, 5]	[4, 5]	[5, 6]	[3, 4]	[5, 6]	[1, 3]	[1, 3]	[4, 5]	[5, 6]	[3, 4]	[4, 5]
9	[4, 5]	[1, 3]	[3, 4]	[6, 9]	[3, 4]	[1, 3]	[4, 5]	[3, 4]	[4, 5]	[3, 4]	[1, 3]	[5, 6]
10	[4, 5]	[5, 6]	[4, 5]	[4, 5]	[3, 4]	[1, 3]	[4, 5]	[4, 5]	[4, 5]	[4, 5]	[3, 4]	[1, 3]

4.D Criteria Weight

Table 4.D.1: Weight of criteria and sub-criteria

Criteria	Criteria Weight	Sub-criteria	Sub-Criteria Weight	Sub-Criteria Global Weight (w)	Priority
Service (C1)	0.567	Technical support (SC1)	0.273	0.155	2
		Information sharing (SC2)	0.067	0.038	8
		Warranty & claim policy (SC3)	0.503	0.285	1
		Capabilities (SC4)	0.156	0.089	5
Relationship (C2)	0.077	Honesty (SC5)	0.593	0.046	6
		Reputation (SC6)	0.242	0.019	9
		Trust & partnership (SC7)	0.134	0.010	11
		Ease of communication (SC8)	0.030	0.002	12
Flexibility (C3)	0.356	Product mix flexibility (SC9)	0.125	0.045	7
		Volume flexibility (SC10)	0.407	0.145	4
		Process flexibility (SC11)	0.041	0.015	10
		Service flexibility (SC12)	0.427	0.152	3

4.E Input Parameters

Table 4.E.1: Input parameters for slow movers

Parameters		Values	Units
Plant, $i \in I$			
Demand	λ_i	: U(40, 100)	unit/year
Setup costs	o_i	: U(500, 1000)	\$/order
Holding costs	h_i	: U(10, 15)	\$/unit/year
Shortage costs	s_i	: U(30, 50)	\$/unit/year
Imperfect items' holding costs	h'_i	: U(30, 50)	\$/unit/year
External failure costs	a_i	: U(5, 7.5)	\$/unit
Location		: [U(0, 500), U(0, 500)]	
Supplier, $j \in J$			
Supply capacity	b_j	: U(100, 300)	unit
Imperfect rate	k_j	: U(0.10, 0.20)	
Vehicle capacity	u_j	: U(60, 90)	unit/vehicle
Disruption frequency	θ_j	: U(1, 7)	days
Disruption length	v_j	: U(0.5, 2)	days
Contractual costs	f_j	: U(10000, 17000)	\$
Unit purchasing costs	c_j	: U(25, 60)	\$/unit
Location		: [U(0, 500), U(0, 500)]	
Plant-Supplier, $i \in I, j \in J$			
Fixed transportation costs	p_{ij}	: U(250, 500)	\$/order/vehicle
Variable transportation costs	r_{ij}	: U(0.75, 3)	\$/mile/vehicle
Lead time	l_{ij}	: $\left(\frac{U(1,2)}{60}\right)d_{ij}$	hours

Chapter 5
Conclusions and Future Research

5.1 Conclusion

5.1.1 Supplier Selection Framework

This dissertation provides a theoretical framework that is useful to deal with the supplier selection process, particularly in determining the critical dimensions so that the problem can be appropriately formulated and solved. Holding the principle of Kraljic's purchasing classification and incorporating the concept of production policy, the framework is proposed to fit the different types of items comprising different importance levels of purchasing and different production and supply complexities. Over 150 published papers focusing on supplier selection have been discussed in light of the novel framework.

Four main dimensions in supplier selection are disclosed, including sourcing strategy, selection criteria, decision scope, and decision environment. A particular type of items can be sourced from a single or multi-suppliers under either single or multi-period. Suppliers' performance can be assessed under qualitative and quantitative criteria, including cost, quality, technology, environmental, risk, flexibility, service, relationship, and social. Order allocation, transportation, inventory management, production planning, and material flows within reverse logistics or closed-loop supply chain are main supply chain activities interrelated with supplier selection. Sources of uncertainty incurred in supplier selection can be distinguished into DM's judgment, supplier-buyer parameters, and managerial goals.

A number of different approaches have been proposed to tackle supplier problems. Some stand-alone and hybrid approaches have some limitations to address a particular dimension. Depending on these dimensions, an appropriate approach can be used to tackle supplier selection for a particular type of item.

In addition, the literature review explores the research avenues. It indicates some research trends that become the driving forces on supplier selection. It promotes an advanced and futuristic perspective to deal with supplier selection in the current challenging environment.

Finally, the first research question (RQ1) is concluded as follows:

Concluding Remark RQ1

RQ1.1: *Supplier selection problems should be formulated with respect to the sourcing strategy, selection criteria, decision scope, and decision environment. These dimensions are distinctive for different types of items depending on the complexity of supply, importance of purchasing, and production policy. Sourcing strategy and selection criteria play a role in the extension of the decision scope*

RQ1.2: *Supplier selection problems can be solved using either a stand-alone or hybrid approach that accommodates sourcing strategy, criteria, decision scope, and decision environment that correspond to each type of item. A hybrid approach is suitable for dealing with the problems that concern a high supply complexity and high purchasing importance. A stand-alone approach can be used to tackle the problem which constitutes a low supply complexity.*

5.1.2 Supplier Selection Models for Strategic Items and Its Solution Approaches

Models for supplier selection focusing on strategic items in MTS environment are proposed according to the suitable framework. These models represent an appropriate problem statement for the respective supplier selection dimensions. High risk of supply (i.e., disruptions) arising from strategic items can be mitigated by properly implementing sourcing strategy, which is multi-sourcing. To foster profitability impact, selection criteria should be evaluated under monetary-based orientation. The strategic items require a relationship with suppliers that benefits to sustain strategic development initiatives. Non-monetary based evaluation is also considered important for strategic items' suppliers. Depending on the criteria and sourcing strategy, supplier selection decisions constitute a large scope for strategic items. As a supply risk mitigation strategy, inventory management is vital to ensure continuity of supply in MTS. Uncertainty emergence can vary for this type of items due to its complex supply and stochastic demand in MTS.

The first model addresses the supply risk (disruption and other risk factors) and uncertain supplier-buyer related parameters. The main issues related to finding adequate deals for material supply, generally involve risk-related quality and delivery. Material supply might include imperfect items, and order delivery might be delayed due to a disruptive event occurred at the suppliers' facilities. Procurement managers might give specific instructions on handling imperfect items, such as separating perfect and imperfect items and storing them in different warehouses. As a result, the holding costs for perfect and imperfect items might be different. Strategic initiatives, such as appropriate supplier selection, can help to reduce the number of imperfect items. In addition, disruption management strategy through multi-sourcing and inventory management can help to mitigate the risks associated with supply, such as delivery delays, by improving the replenishment. Considering TL transportation, which has been applied in general practices and imperfect quality with specific holding costs, this study proposes a supplier selection model integrated with inventory management under disruptions.

We develop a simulation-optimization approach to address the problem mentioned before. Analytical model enhancement is used to accommodate the disruptions, impacting the replenishment and order arrival as the deliveries are delayed, through enhancing reorder point based on the refined lead time. This approach focuses on implementing a mitigation strategy to address disruptions during a supply chain's proactive stage. It also provides comprehensive decision-making by encouraging proper supplier selection while simultaneously determining order allocation and inventory decisions. The demand uncertainty and disruptions are incorporated in the simulation to estimate the total costs of the solutions. The proposed approach can help refine the lead time in inventory management and supplier selection, particularly when shortages are costly. In other words, mitigating the risk of supply disruptions by considering the disrupted lead time to improve the reorder point contributes to a better inventory performance and more selective suppliers. Nevertheless, this reactive strategy is more beneficial in protecting against disruptions and reducing their impact, namely when the disruptions are frequent and short.

The second model extends the previous model enhancing the incorporation of selection criteria and decision environment. Due to high-profit impact and supply complexity, the second model addresses a supplier selection problem incorporating criteria holistically, including qualitative and quantitative, as well as tackling DMs judgment uncertainty. In addition to the quantitative criteria, three criteria and 12 sub-criteria associated with the qualitative measure are considered.

A novel two-phase solution approach is proposed to solve the second model with multi-objective. Fuzzy AHP and interval TOPSIS are respectively used to perceive imprecise DMs' judgment in determining weight and assessing suppliers under qualitative criteria. The final decision-making process is performed using S-O based on analytic model enhancement (AME). AME provides a better decision for supplier selection and inventory management since the lead time is refined according to the disruption information. In other words, this solution approach is useful to deal with disruption risk mitigation.

The second (RQ2) and third (RQ3) research questions are summarized as follows:

> ***Concluding Remark RQ2:*** *Supplier selection for strategic items requires holistic consideration, which can be assessed into monetary and purchasing values, integration, and initiative to mitigate supply risk in order to improve a firm's competitive advantages as a whole. This problem can be formulated as mixed integer with a single objective and multi-objective models*

> ***Concluding Remark RQ3:*** *The proposed hybrid approach, namely S-O, handles disruptions and uncertain supplier-buyer parameters, as well as incorporates quantitative criteria well. The hybrid MCDM and S-O approach has also proved to solve comprehensive selection criteria, complex sourcing*

strategy, integrated decision scope, and different sources of uncertainty effectively.

5.1.3 Managerial Insights

Our analysis draws important implications for decision-makers in supplier selection. It emphasizes critical dimensions in the supplier selection process, including criteria and approach. Based on the first model analysis, supply capacity, contractual costs, imperfect rate, vehicle capacity, purchasing costs, and lead time are significant factors influencing supplier selection for strategic items. However, the criteria importance should be given a different priority depending on the importance of purchasing (i.e., fast-moving and slow-moving items). Supply capacity and contractual costs are the critical elements of the supplier selection process. Moreover, when contractual costs influence the system costs, supply capacity variability is crucial to the trade-off. Procurement managers should also focus on vehicle capacity when selecting suppliers for fast-moving items. Furthermore, in the presence of supply disruptions, procurement managers should pay more attention to the suppliers whose imperfect rate is relatively low to safeguard the more significant shortage concerning slow-moving items. In addition, the interaction of these parameters is also considered significant. More specifically, there is a trade-off among the criteria that highly depends on its weight or importance.

The analysis performed in the second model also brings insightful implications regarding the trade-off between quantitative and qualitative criteria. It is difficult for strategic items to compromise quantitative criteria since it contributes to a firm's core performance (e.g., quality, delivery, and cost) and triggers monetary risks that impact inventory decisions.

5.2 Future Research

This study has limitations that might lead to interesting future research. Although the study has addressed the risk factors (i.e., disruptions, imperfect quality, delivery delay), other risk factors in global sourcing might also exist due to political or social instability. The future study can be extended, considering this aspect to sustain resilient supplier selection in global sourcing. Furthermore, the increase of sustainability awareness might compel firms to identify related criteria and incorporate them into supplier selection. Developing a framework for supplier evaluation under sustainability could also be an interesting future research direction. Current work can also be extended in several ways, including implementing other disruption mitigation strategies, such as backup sourcing, and incorporating other disruption risk factors, such as increased purchasing prices and the change of suppliers' capacity.

Despite the vast growth of supplier selection studies, there are still many research opportunities in the supplier selection area, particularly in the integrated selection problems, hybrid solution methods, and sustainability goals. According to the literature review, future work can focus on the following to develop distinctive models.

i) Integration of supplier selection and vehicle selection with multi-sourcing, single period, multi-items for bottleneck and strategic items considering uncertainty in MTO/ ATO/ MTS production policy;

ii) Integration of supplier selection and inventory management with multi-sourcing for strategic or bottleneck items with multi-item under joint replenishment in ATO and MTS production policies;

iii) Integration of supplier selection with a single sourcing strategy, multi-period for leverage items in ATO/ MTS production policy under uncertainty;

iv) Integration of supplier selection and material flow in reverse logistics considering sustainability with multi-period models under uncertainty.

The fourth research question (RQ4) is emphasized as follows.

Concluding Remark RQ4: *Some driving forces have been indicated from the literature related to the selection criteria, decision environment and decision scope. These driving forces include fostering supply chain resilience through risks mitigation, embracing sustainability goals, integrating supply chain processes, and considering distributed ledger technology adoption.*