Value-Driven Performance Management in SMEs: Optimising Supply Chain Processes through the Transition from Industry 4.0 to 5.0 and Addressing Implementation Challenges

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Nomenclature

SME	Small-medium Enterprise
IoT	Internet of Things
AI	Artificial Intelligence
NSGA-II	Non-dominated Sorting Genetic Algorithm II
DEAP	Distributed Evolutionary Algorithms in Python
PSO	Particle Swarm Optimisation
MILP	Mixed Integer Linear Programming
KPI	Key Performance Indicator
TTS	Time to Solution
NPS	Net Promoter Score
OTD	On-time Delivery
ACO	Ant Colony Optimisation
JIT	Just-in-time
JIC	Just-in-case
ERP	Enterprise resource planning
RFID	Radio Frequency Identification
USP	Unique Selling Point

Abstract

This dissertation investigates the shift of Small-Medium Enterprises (SMEs) in the automotive industry from Industry 4.0 to Industry 5.0, focusing on optimising supply chains through the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The research explores how value-driven metrics can be integrated into existing technologies to facilitate this transition. Industry 4.0's emphasis on automation and data exchange provides the technological foundation, while Industry 5.0 introduces a human-centric approach, prioritising sustainability and collaboration. This study highlights the challenges SMEs face, limitations in operational capabilities, knowledge and computational resources. By understanding these limitations, the research refines algorithms to enhance supply chain efficiency and adaptability. The findings provide a practical framework for SMEs, demonstrating how technological advancements can be aligned with value-driven goals to improve operational performance and sustainability. The methodological approach includes quantitative analysis using NSGA-II, modified to address automotive SME capabilities and their limitations. This adaptation not only ensures the relevance of the solutions but also their applicability in dynamic market conditions. Also qualitative to highlight the adaptation strategies and constraints. Key conclusions highlight the possibilities of incorporating algorithms into the SME supply chain and value-driven metrics leads to more resilient and competitive operations through forecast and customer insights. The research contributes to both academic and practical fields by offering strategies that SMEs can implement to thrive in a digitally transformed landscape. Future work includes exploring the scalability for large corporations of the adapted algorithms and their long-term impacts on SME performance. Further research could also examine the interplay between automated solutions and human oversight in optimising supply chain decisions.

Keywords: Industry 4.0, Industry 5.0, Automotive SMEs, Supply Chain Optimisation, Reinforcement Learning, Value-Driven Performance.

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1 Introduction

1.1 Background Context

The modern automotive industry stands at the forefront of extraordinary technological innovations, driven by the advancements of the fourth industrial revolution. This era, known as Industry 4.0 has developed a period of unprecedented automation, manufacturing technologies and extensive data exchange, the fundamentals that shaped the sector's landscape (Schwab 2017). Within this revolutionary framework, Small and Medium-sized Enterprises (SMEs) represent an integral portion of this sector, particularly in terms of supply chain network and employment within the industry representing 90% of businesses and 50% of businesses worldwide (WTO 2016). However, as the industry shifts towards a more human-centred, value-driven, and intelligent manufacturing environment—signifying the dawn of Industry 5.0. SMEs face the challenge of embracing these changes while preserving the agility and innovation that gives them a competitive edge (Madhavan et al. 2024).

Feature	Industry 4.0	Industry 5.0
Focus	Automation and connectivity	Human-machine collaboration
Goals	Efficiency, agility, and productivity	Sustainability, resilience, and social responsibility
Technologies	IoT, AI, big data analytics	IoT, AI, big data analytics, human-centred design
Benefits	Reduced costs, improved quality, faster time to market	Increased job satisfaction, improved safety, reduced environmental impact

Table 1: Comparison between Industry 4.0 and Industry 5.0 (Adapted from Nair (2023))

Industry 5.0, first introduced at the CeBIT 2017 trade fair in Hannover, Germany, materialised from the ideology that a purely technocentric approach is not fully sustainable for modern society and economies. Shown in Table 1, Industry 4.0 focuses more on the optimisation of smart machines and automation, Industry 5.0 prioritises the synergy between automated systems and human-centric industrial processes. It seeks to find a balance, highlighting values such as sustainability and personalised customer requirements (European Commission 2021). For SMEs, transitioning to Industry 5.0 presents an opportunity to adopt technologies that integrate human values into business operations and a challenge due to their inherent resource limitations (Mourtzis et al. 2022).

This dissertation explores the potential of algorithmic models to optimise SME supply chains in the automotive industry. Despite current algorithmic models proven to have high efficacy in enhancing decision-making and operational efficiency, there is a noticeable knowledge gap in their application within the SME context, which this dissertation aims to address (Lee & Lee 2015, Ghobakhloo et al. 2022). This investigation explores and adapts algorithmic models to SME operational needs and parameters, integrating Industry 5.0's value-driven metrics with Industry 4.0 technologies. The aim is to enhance supply chain efficiency in SMEs, aligning technological advancements with human-centric values.

The transition from Industry 4.0 to 5.0 also presents a gap that requires closer examination of how SMEs can adapt to remain competitive and efficient. While Industry 4.0 focuses on integration of automotive systems and the Internet of Things (IoT), Industry 5.0 introduces a collaborative model between humans and machines, emphasising personalisation and sustainability (Kagermann et al. 2013, Xu, Lu, Vogel-Heuser & Wang 2021). Understanding how SMEs can navigate this transition effectively is crucial, as they often lack vast resources that are essential for innovation and exponential economic growth (Mourtzis et al. 2022). Research suggests that tailored algorithmic approaches that integrate this shift may hold the key in addressing these challenges by providing scalable solutions that align with the dynamical system and capabilities of SMEs.

In summary, as the automotive industry progresses towards industry 5.0, a deeper understanding of the role of SMEs and their capabilities in optimising supply chain efficiency through algorithmic models becomes paramount. This study aims to adapt these models to a more human-centric and value-driven framework, positioning it at the core of the transition challenge facing SMEs today.

1.2 Aims & Objectives

The overall aim of this dissertation is to investigate the adaptation and scalability of algorithmic models to assist SMEs in the automotive industry during the transition from Industry 4.0 to 5.0, with emphasis on optimising supply chain performance with value-driven metrics. To achieve this aim, this dissertation will have the following objectives:

1. **Methodological Analysis:** Define and apply a methodological framework for assessing and refining the qualitative findings on Industry facts, SMEs and supply chain algorith-

mic models. Outlining data collection, knowledge synthesis, analysis techniques, and evaluation methods aligned with the following objectives.

2. **Evaluate Current Algorithmic Applications:** Analyse existing algorithmic models for supply chain optimisation, establish performance criteria for these models, and identify improvement areas and gaps between current capabilities and future needs.

3. **Identify the Limitations of Current Supply Chain Optimisation Algorithms for SMEs in the Automotive Industry:** Investigate how existing supply chain optimisation algorithms, predominantly employed by large corporations fail to meet SMEs' specific needs. Focusing on scalability, cost-effectiveness, and implementation complexity.

4. **Identify Adaptation/Scalability Requirements For Automotive Sector:** Determine the specific requirements for SMEs in the automotive sector to adapt algorithmic models implementing Industry 5.0 paradigm and Industry 4.0 technologies, emphasising enabling human-machine collaboration and integrating value-driven metrics like sustainability and customisability.

5. **Adapt and Scale Current Algorithms:** Modify an existing algorithm tailored for SMEs' supply chain optimisation needs. Involves detailing the algorithmic structure, incorporating value-driven metrics to align with Industry 5.0, and integrating Industry 4.0 technologies. Focus on adapting these models to SME-specific parameters and scenarios.

6. **Propose Implementation and Adoption Strategies:** Propose practical strategies for implementing the adapted algorithm within the operational constraints of SMEs, including deployment, employee training, and scalability as the business grows or industry standards evolve.

These objectives on bridging the gap between the solutions available to large corporations and the practical realities of SMEs. It sets the foundations of this dissertation, underscoring the importance of developing adaptable and scalable algorithmic models that cater specifically to the needs of SMEs in the automotive industry transitioning towards Industry 5.0.

1.3 Research Question

Accounting for the dissertation aim and objectives a general research question is developed.

> "Given the evolving landscape from Industry 4.0 to Industry 5.0, how can existing algorithmic models be adapted and effectively scaled to support Small and Medium-sized Enterprises (SMEs) within the automotive sector, specifically to enhance supply chain efficiency through the integration of value-driven performance metrics?"

1.4 Project Scope and Delimitation

To maintain the focus of this dissertation, several delimitations have been imposed. The project scope encompasses:

Industry Limitation: This research is primarily focused on the automotive sector, reflecting the significant role of SMEs and addressing their unique supply chain challenges. While the core principles of the algorithms are explored within this industry, parameters and other necessary values may be approximated from general SME data due to potential resource limitations.

Enterprise Size: The study is limited to SMEs, recognising their distinct operational dynamics and constraints. However, general knowledge and algorithms developed for larger enterprises will be considered for their potential to be adapted and scaled to fit the SME context.

Geographical Boundaries: While the research outcome may be extrapolated to wider adoption, this research may focus in a specific region or country due to research resource and case study limitations.

Technological Scope: The study will be limited to algorithmic models pertinent to supply chain optimisation, other potential applications of algorithms in SMEs are outside the purview of this study.

Historical Frame: Empirical data collection and simulation analyses will focus on the period from 2011—the inception of Industry 4.0—to the present, to maintain relevance to the present automotive sector and SMEs' operational contexts. This does not preclude the inclusion of foundational theories and established definitions, such as those concerning algorithms, which have historical roots extending well before 2011.

Temporal Frame: The research examines the current transition phase, acknowledging that industry standards and technologies are continually being innovated.

This study will not cover the complete digitisation of SMEs or the broader impacts of the shift to Industry 5.0 on organisational philosophies and employee roles beyond the supply chain context.

1.5 Significance of Study

The importance of this study encompasses a wide range, impacting multiple stakeholders within the broader field of the automotive industry and possibly other industrial operations:

For SMEs in the Automotive Sector: This research provides SMEs in the automotive sector with practical strategies to adopt algorithmic models effectively, enhancing supply chain efficiency in a landscape transitioning to Industry 5.0. Addressing niche SME constraints and how to tackle them.

Academic Contribution: The research aims to contribute relevant academic discourse by filling identified knowledge gaps from the following literature review, particularly in the application of Industry 5.0 ethos to SMEs and the adaptation of current algorithmic supply chain optimisation solutions to smaller enterprises.

Value-driven Performance Insights: This research highlights value-driven metrics in supply chain optimisation algorithms, shedding light on the potential for these models to encapsulate broader business values, including sustainability, customisation and social impact, thus offering a holistic approach to supply chain management.

Industry 5.0 and 4.0 Insights: By addressing the challenges SMEs face during the shift to Industry 5.0, this research aims to provide insight between the interplay of technological advancement and human-centric manufacturing processes.

Future Research: The contents of this research may be used as a foundation for future research into the adaptability of the current broader field of technological innovations for SMEs.

This research is aimed to contribute practical and theoretical insights that not only aid SMEs in their transition to Industry 5.0, but also provide foundations for future academic and industry-specific explorations into efficient, value-driven supply chain optimisation in an era of continuous technological innovation.

2 Literature Review

This chapter will analyse and evaluate current academic literature, academic journals, industry reports, and theoretical frameworks related to algorithmic supply chain optimisation, focusing on the automotive industry as it progresses from Industry 4.0 to 5.0. It aims to understand how this industrial transition affects SMEs and the role that algorithmic models can play in optimising supply chain efficiency as it integrates with value-driven metrics. The literature review methodically structured to cover relevant subtopics and provide a comprehensive understanding of:

1. **Transition from Industry 4.0 to Industry 5.0: Implications for Automotive SMEs:** Exploring the conceptual and practical differences between Industry 4.0 and 5.0, and their implications for the automotive sector

2. **Supply Chain Optimisation Requirements for automotive enterprises:** Exploring the optimisation objectives of Automotive SMEs, potential improvements and parameters

3. **Algorithmic Supply Chain Optimisation Models:** Reviewing the current algorithmic models for supply chain optimisation, identifying key criterias

4. **Criteria for Optimal Supply Chain Optimisation in SMEs Versus Large Corporations** Exploring the unique supply chain optimisation needs and criteria of SMEs in contrast to large corporations.

5. **Challenges and Possibilities for SMEs in Developing, Adapting, or Scaling Models:** Investigating the setbacks and prospects in tailoring supply chain optimisation models to cater to the needs of SMEs, considering constraints and strategic priorities

This systematic literature review aims to identify gaps in the current body of knowledge and underscore the research objectives outlined in Chapter 1.2. It sets a solid foundation for the subsequent synthesis of knowledge to be based upon theoretically and practically.

2.1 Transition from Industry 4.0 to Industry 5.0: Implications for Automotive SMEs

The transition from Industry 4.0 to Industry 5.0 marks a significant shift in the manufacturing landscape, evolving from focusing on technological automation to integrating human creativity with machine efficiency. This change is particularly crucial for SMEs—typically having fewer than 250 employees—representing 99% of businesses in Europe, of which 10.2% is the automotive sector. These SMEs face the dual challenges of integrating Industry 4.0 technologies and adapting to Industry 5.0 human-centric models. Shown in Figure 1, Europe's SME automotive sector employs 7.8 million people, accounting for 57% of total employment in this sector, highlighting the critical role of SMEs within this industry (Di Bella et al. 2023).

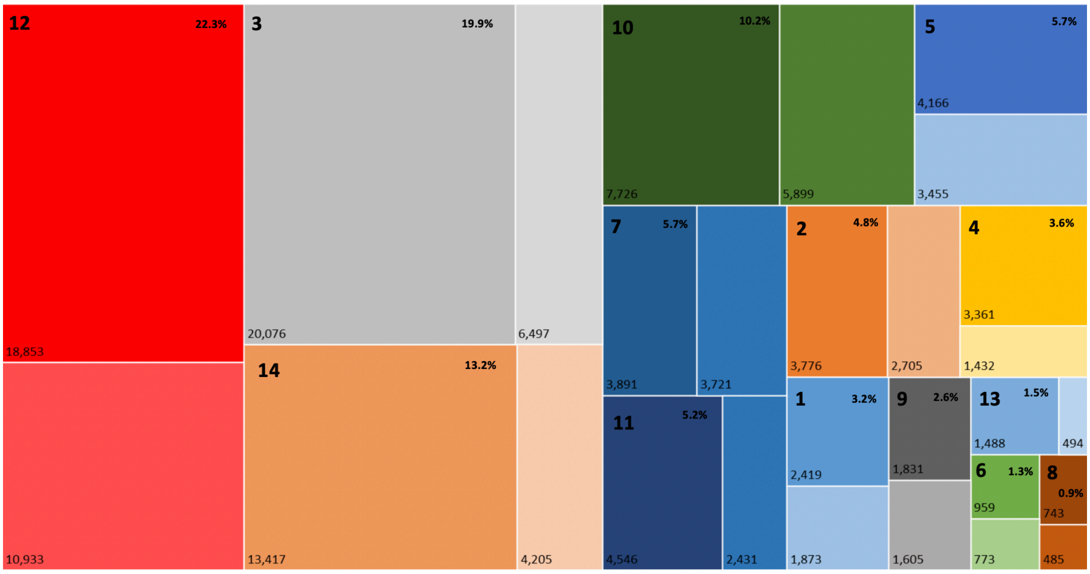


Figure 1: Number of individuals (in thousands) per ecosystem employed by SMEs and large enterprises and percentage of ecosystem employment in total employment of the 14 ecosystems 2022 *Note: The industrial ecosystems are as follows: 1 - Aerospace and Defence; 2 - Agri-food; 3 - Construction; 4 - Cultural and Creative Industries; 5 - Digital; 6 - Electronics; 7 Energy-Intensive Industries; 8 - Energy Renewables; 9 - Health; 10 - Mobility-Transport-Automotive; 11 - Proximity, Social Economy and Civil Security; 12 - Retail; 13 - Textiles; 14 - Tourism. Mobility-Transport-Automotive covers production of motor vehicles, their repairs and transport* (Taken from Di Bella et al. (2023))

Industry 4.0 technologies such as 3D printing, the Internet of Things (IoT), and big data analytics have brought significant operational efficiencies and transparency to automotive manufacturing (Dirican 2015, Papulová et al. 2022). However, the technology-centric focus of Industry 4.0 has been critiqued for overlooking human values, which Industry 5.0 aims to re-integrate. The evolved model emphasises collaboration, sustainability, and customisation, aligning with the increasing consumer demand for ethically produced and personalised products (Xu, Lu, Vogel-Heuser & Wang 2021, Breque et al. 2021). Table 1 highlights Industry 4.0 and 5.0 not as distinct phases but as part of a continuum, propelling the industry into a future where technology and human values are inextricably linked.

The shift towards Industry 5.0 has profound implications for automotive SMEs. In a limitation study on Industry 5.0 by Adel (2022), it is highlighted that this transition requires them not only to adopt new technologies but also to significantly alter their operational paradigms. This includes transitioning from traditional production methods to more flexible, customer-oriented, and environmentally sustainable practices. For example, an automotive case study highlighted how the integration of IoT with real-time data analytics enhances operational flexibility and reduces waste, significantly improving both customer responsiveness and environmental impact (Vu & Nguyen 2022, El Jaouhari et al. 2023).

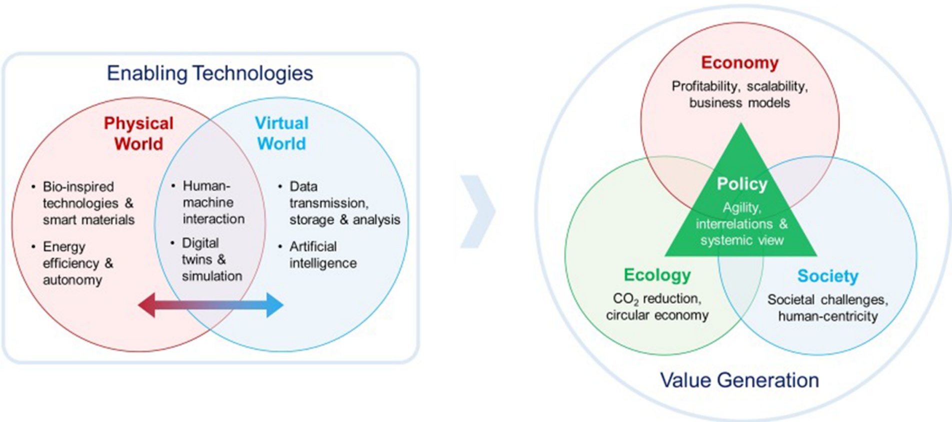


Figure 2: Industry 5.0 values and Industry 4.0 technological enablers (Adapted from Xu, Lu, Vogel-Heuser & Wang (2021))

Automotive SMEs, as shown in Figure 2, adapts to Industry 5.0 by leveraging both Industry 4.0's technological foundations and the new human-centric ideals of Industry 5.0. This includes adopting metrics such as the Net Promoter Score (NPS) to gauge customer satisfaction and monitoring On-time Deliveries (OTD) to enhance supply chain efficiency (Reichheld 2011, Yadav & Goel 2008, Carvalho et al. 2022). Another example includes an automotive industry in Germany that integrated these metrics with Industry 4.0 technologies, facilitating a transition to Industry 5.0, which led to improved customer retention and supply chain reliability without sacrificing efficiency (Hunke & Prause 2014).

While the literature review provides valuable insights into Industry 4.0 and 5.0 technologies and their applications, it also reveals a significant gap in strategic frameworks that effectively guide SMEs through this transition. Specifically, there is a lack of strategies that leverage human-machine collaboration for more adaptable and optimised supply chain solutions. This limitation underscores the need for further exploration into innovative strategies that can help SMEs innovate and remain competitive in the industry. In summary, the transition to Industry 5.0 presents both opportunities and challenges for automotive SMEs, necessitating a thorough reevaluation of their operational and strategic approaches. By embracing Industry 5.0 principles and integrating value-driven metrics with technological advancements, SMEs can gain a competitive edge, ensuring long-term sustainability and ethical operations in a rapidly evolving industrial landscape.

Aspect	**Key Takeaway**
Technological Shift	Industry 4.0: IoT, advanced robotics and big data analytics Industry 5.0: value-driven, customisation and sustainability
Operational Changes	Shift from traditional manufacturing to flexible, sustainable practices.
Human-Centric Models	Increased focus on collaboration, customisation, and sustainability.
Impact on SMEs	Need for SMEs to adopt new technologies and alter operational strategies.
Case Studies	Examples of SMEs integrating new technologies to enhance efficiency/sustainability and customer responsiveness (e.g., real-time data analytics).
Strategic Gaps	Lack in strategic frameworks to guide SMEs through the transition, underscoring the need for innovative strategies.

Table 2: Summary of literature review on the transition from Industry 4.0 to Industry 5.0 as discussed in Section 2.1 (Own work)

2.2 Supply Chain Optimisation Requirements for Automotive SMEs

The automotive industry faces unique challenges and opportunities in supply chain management due to its complex manufacturing processes and extensive logistic networks (Meyr 2009). This literature review explores the prominent objectives of supply chain optimisation in the automotive sector, considering the impact of these objectives on both SMEs and large corporations.

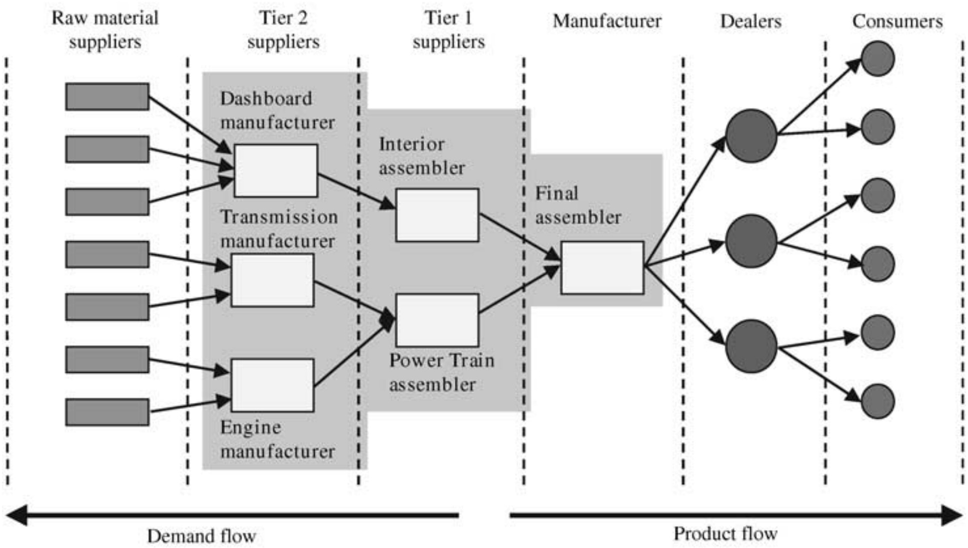


Figure 3: A generic automotive supply chain scheme, displaying its vast logistic networks and manufacturing lines (Taken from Chandra & Kamrani (2004))

As with all businesses, automotive companies prioritise traditional business metrics such as revenue growth, cost minimisation, and profit margins. These financial metrics are foundational for gauging business health and market competitiveness (Dinsdale & Bennett 2015). A paper by Dias et al. (2019) indicated that waste reduction and streamlining production processes could reduce production costs, directly influencing gross margins and operating profits. Similarly, optimising pricing strategies and sales operations to maximise revenue per unit sold is crucial for sustaining business growth and profitability. Understanding operating objective trade-offs is a common practice that helps make financial and operational decisions (Qamar et al. 2020, Vamsi Krishna Jasti & Sharma 2014).

In the automotive sector, maximising production efficiency and minimising costs are crucial. Companies aim to streamline operations, minimise waste, and leverage economies of scale to reduce costs (Qamar et al. 2020). For instance, the adoption of just-in-time (JIT) manufacturing and lean production techniques, producing amounts based on customer demand, has been widely implemented to reduce inventory costs and increase operational agility, which is critical to SMEs, impacting operational key performance indicators (KPIs) like inventory turnover rates and transportation costs (Aghazadeh 2003, Saliji 2021). Moreover, robotic automation and AI-driven logistics further streamline manufacturing and distribution, enhancing efficiency and precision (Dash et al. 2019).

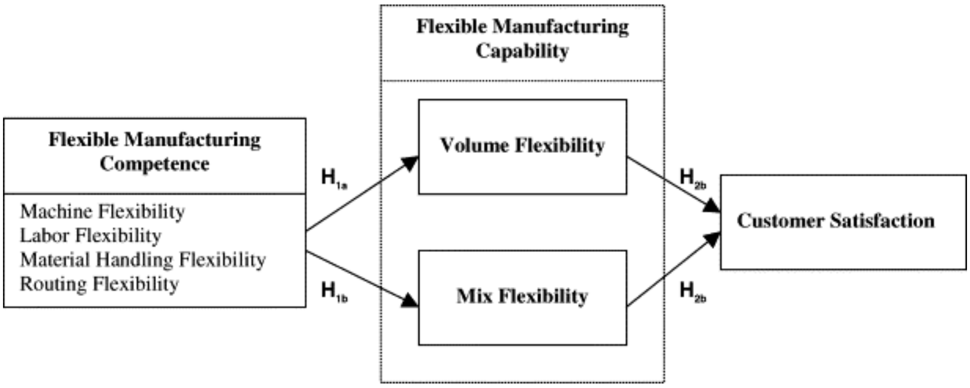


Figure 4: Impact of flexible manufacturing competence on capability and customer satisfaction. (Taken from Zhang et al. (2003))

In response to evolving consumer demands for customised and technologically integrated vehicles, automotive companies must enhance supply chain flexibility and responsiveness. KPIs such as on-time delivery (OTD) rates, cycle time and lead time are pivotal in maintaining customer satisfaction and competitiveness in the market (Zhang et al. 2003). This involves agile supply chain practices that can quickly adjust to changes in demand, effectively managing inventory and production schedules. Additionally, the accuracy of demand forecasts is pivotal, allowing companies to align their production with market needs, thereby reducing excess inventory and improving resource allocation. Advanced data analytics support these efforts by enabling more accurate predictions and responsive supply chain adjustments, which are crucial to meeting customer expectations in the dynamic market environment (Yildiz et al. 2016, Rožanec et al. 2021).

Maintaining high-quality standards and compliance with international regulations while building resilience is critical in the automotive industry. The industry employs quality control systems, including predictive maintenance algorithms, which monitor and maintain product quality, reduce defect rates, and manage recall costs effectively (Hachem et al. 2021, Mehrdad Mohammadi & Tavakkoli-Moghaddam 2015). Operational metrics such as downtime duration, cycle time, and recovery time objective (RTO) are critical for resilience, as minimising production and delivery disruptions directly impacts supply chain integrity and customer trust (Zhang et al. 2003). Satisfaction in quality and flexibility can also be quantified by net promoter score (NPS) and brand loyalty, understanding customer responses based on supply chain operation (Baquero 2022).

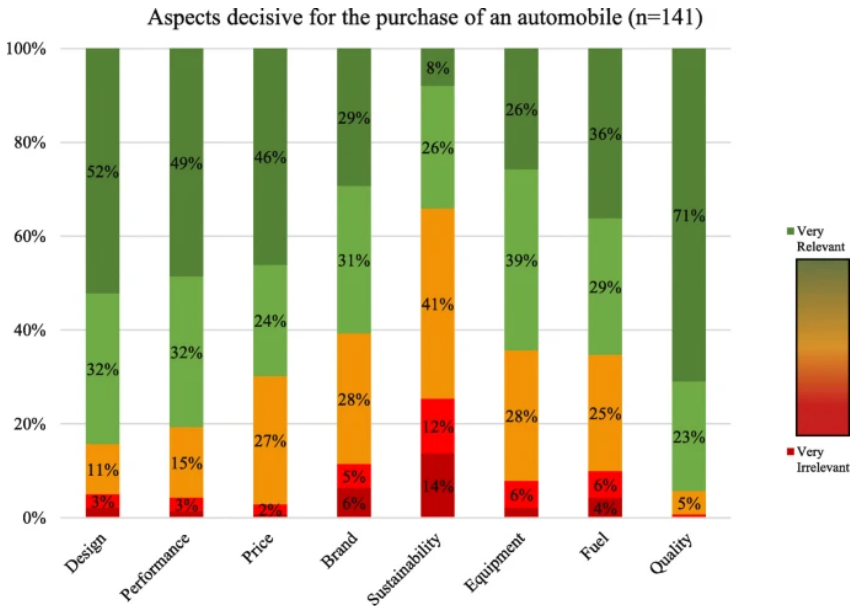


Figure 5: Aspects decisive for the purchase of a passenger car. (Taken from Wellbrock et al. (2020))

Due to growing environmental concerns and regulatory requirements, sustainability has become a significant objective. As shown in Figure 5, in a survey conducted by Wellbrock et al. (2020), from 141 individuals 75% considered sustainability to be relevant and some very relevant in their purchase decision of a car. Automotive companies increasingly focus on reducing carbon emissions, incorporating recycled materials, and optimising supply chain routes to decrease their footprint (Daugherty et al. 2021). Sustainable practices are not only a response to regulatory demands but also a factor in fostering consumer loyalty and protecting brand reputation in a market increasingly sensitive to environmental issues (Xia & Li-Ping Tang 2011). This can also be done by having an ethical environment for employees and shareholders, especially in the rising prominence of value-driven practices in Industry 5.0 (Xu, Lu, Vogel-Heuser & Wang 2021, Breque et al. 2021).

In summary, the automotive sector's supply chain optimisation efforts are driven by a blend of operational, strategic, and financial objectives, each crucial for navigating the complexities of a global market and meeting evolving customer expectations.

Aspect	Key Takeaway
Financial Metrics	Emphasis on revenue growth, cost minimisation, and profit margins as essential indicators of business health and market competitiveness.
Production Efficiency	Focus on optimising operations, reducing waste, and leveraging economies of scale to lower costs. Adoption of JIT and lean production techniques to enhance operational agility.
Robotic Automation	Integration of robotic automation and supply chain algorithms in logistics to increase decision-making efficiency and precision.
Supply Chain Flexibility	Enhancement of supply chain flexibility to meet demands for customised and technologically integrated vehicles.
Forecast Accuracy	Utilisation of advanced data analytics for accurate demand forecasts, improving inventory management and production alignment with market needs.
Quality Control	Implementation of quality control systems to maintain high standards and build resilience.
Environmental Sustainability	Increasing commitment to reducing carbon emissions, using recycled materials, and optimising supply chain routes to enhance sustainability.
Ethical Practices	Fostering an ethical environment for employees and shareholders, aligning with value-driven practices of Industry 5.0.

Table 3: Summary of literature review on supply chain optimisation requirements for automotive SMEs as discussed in Section 2.2 (Own Work)

2.3 Algorithmic Supply Chain Optimisation Models

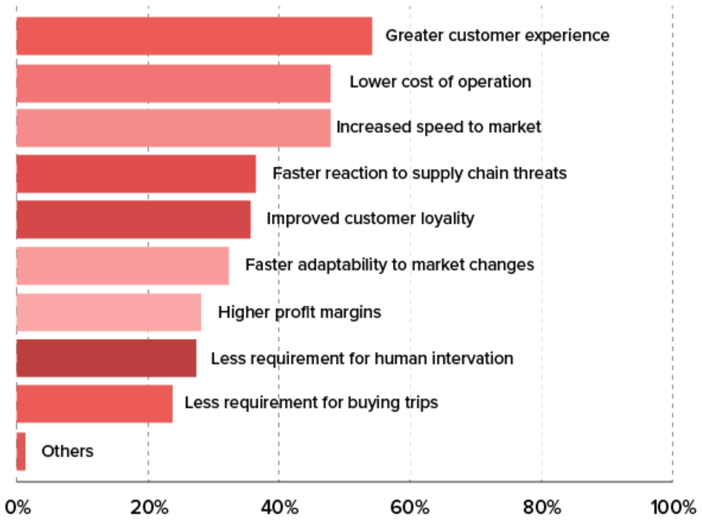


Figure 6: Benefits of digitising supply chain, including through IoT, AI, blockchain, algorithm optimisation and robotics. (Taken from Singh (2024))

Adopting algorithmic models has significantly revolutionised supply chain management in the automotive industry. As shown in Figure 6, algorithmic models enhance decision-making processes across logistics, inventory management, and production scheduling, catering to the company's need for efficiency and responsiveness. Based on a book by Christou (2011), it can be categorised into three types. Heuristic and metaheuristic algorithms solve complex, non-linear optimisation challenges and are ideal for dynamic environments and multi-objective problems like route optimisation and resource allocation. Mathematical programming algorithms systematically optimise resource allocation under constraints, crucial for detailed planning in production scheduling, inventory management, and logistics. Predictive algorithms are essential for forecasting market trends and managing supply chain uncertainties. These models use historical data to predict future trends, optimise inventory, and enhance demand responsiveness (Christou 2011).

Heuristic and metaheuristic algorithms tackle complex optimisation problems that are challenging for conventional approaches. For instance, genetic algorithms (GA) have been employed to optimise supplier selection and procurement processes, which are suitable for multi-objective optimisation but require careful parameter tuning and are somewhat slow to converge (Ehtesham Rasi & Sohanian 2021, Mehrdad Mohammadi & Tavakkoli-Moghaddam 2015, Altiparmak et al. 2006, Babaveisi et al. 2018). Particle Swarm Optimisation (PSO) is utilised to enhance warehouse layout networks for better storage efficiency and shorter transport times, but it may require multiple runs to avoid local optima (Li et al. 2019, Soleimani & Kannan 2015). Similarly, Ant Colony Optimisation (ACO) has been used effectively for dynamic transport routing, though its slower convergence can be a limitation (Zohal & Soleimani 2016, Luan et al. 2019). A paper by Sun & Su (2020) focusing on green logistics, involves NSGA-II, where it was adapted to balance revenue, cost and pollution emissions, thereby optimising resource allocation and reducing transportation times. As shown in Figure 7, with the increase in income, the amount of pollution increases, while some oscillatory behaviour in costs.

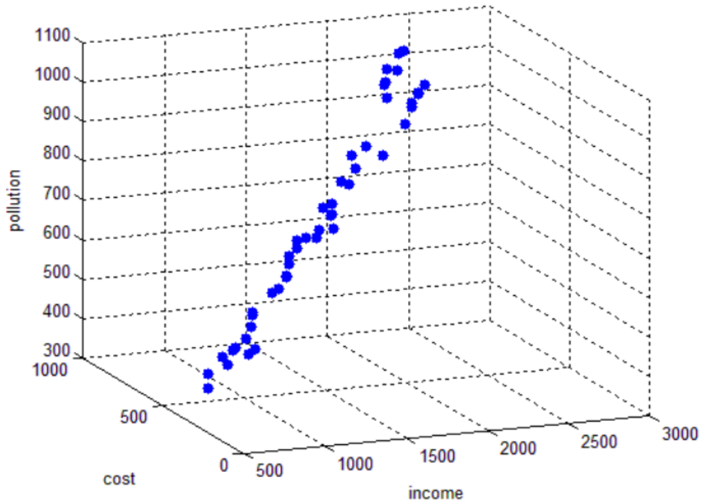


Figure 7: Pareto frontier for the supply chain in large firms, trade-offs between pollution, cost and income. (Taken from Sun & Su (2020))

Mathematical programming algorithms, including Linear Programming (LP) and Mixed Integer Linear Programming (MILP), offer systemised solutions to resource allocation. LP is commonly used to manage production levels and minimise costs within linear operational constraints (Spitter et al. 2005). Oppositely, MILP has been pivotal in detailed scheduling and capacity planning, essential for ensuring that production meets demand, though it may require significant computational resources (Jokinen et al. 2015, Rajak et al. 2022). For example a study conducted by Jokinen et al. (2015) to develop an MILP model for small-scale LNG supply chain optimisation for supply along a costline, the study aims to minimise costs related to fuel procurement and provide an optimal supply chain setup considering satellite port locations, ship sizes and utilisation and customer distribution. Though it highlighted that due to computational demand the model is best used as a decision making tool where solving times of hours, or even days, are acceptable.

Predictive and statistical models are essential for forecasting and adjusting to supply chain uncertainties. Time series forecasting is widely adopted for predicting parts demand, enabling optimised inventory management (Doganis et al. 2008). Simple Moving Average (SMA) and exponential smoothing are applied to rapidly streamline demand predictions and adjust supply strategies (Khosroshahi et al. 2016). However, these models are more widely used for forecasting theoretical business performance, which would lead to a better understanding of product demand; in terms of flexibility on usage, heuristic, metaheuristic, and mathematical algorithms are more versatile.

In conclusion, integrating advanced algorithmic models across the automotive supply chain, from inventory management to logistic divisions, marks a significant shift in how the industry optimises its operations. Heuristic, metaheuristic, mathematical, and predictive algorithms streamline decision-making and ensure that automotive companies remain competitive and responsive to market demands. As the industry evolves, implementing these algorithmic models with monitoring technologies such as IoT and real-time data analytics becomes crucial to maintaining its resilience and adaptivity (Vu & Nguyen 2022, Rezaei et al. 2017).

Algorithm Type	**Key Application and Insights**
Heuristic and Metaheuristic Algorithms	Utilised for complex, dynamic environments and multi-objective problems. Examples include genetic algorithms for supplier selection and procurement, NSGA-II for multi-objective optimisation, PSO and ACO for optimising warehouse layout. Challenges include slow convergence and the need for multiple runs to avoid local optima.
Mathematical Algorithms	Focus on systematic optimisation of resource allocation. Linear Programming is used for managing production levels, while MILP addresses scheduling and production planning, often requiring significant computational resources.
Predictive Algorithms	For forecasting market demands and managing uncertainties, utilising historical data to forecast demand and optimise inventory. Common methods include Time Series forecasting and Exponential Smoothing.

Table 4: Summary of algorithmic supply chain optimisation models discussed in Section 2.3 (Own Work)

2.4 Criteria for Optimal Supply Chain Optimisation in SMEs Versus Large Corporations

The criteria for optimal supply chain optimisation diverge significantly between SMEs and large corporations, reflecting distinct operational scales, resource availability, and strategic goals. Though both are connected through the automotive industrial technologies, as mentioned in Chapter 2.1, Industry 4.0 and 5.0 utilises the same technologies but diverge in their approach. This literature review delineates these differences, highlighting the unique challenges that would enable automotive SMEs to adopt digitisation brought by the technologies in Chapter 2.3 and optimise their supply chain requirements addressed in 2.2.

Attribute	**Large**	**SME**
Organisational Structure	Hierarchical with several layers of management	Flat with few layers of management
Leadership	Involves strategic activities	Involves operational activities
Management Style	Participative	Empowered supervision that commands and controls
Operational Improvement	Is often introduced with a holistic perspective	Is introduced with a partial and fragmentary prospect
Human Resource	Involves continuous training and staff development	Training and staff development is ad-hoc
Networking approach	Extensive and structured external networking	Limited and unstructured external networking
Innovation	Derived by R&D	Derived by clusters and networking

Table 5: Comparison of Attributes between Large Corporations and SMEs (Taken from Poshdar et al. (2019))

Figure 5 highlights the main difference between SME and large corporations. SMEs value agility and flexibility in their supply chain operations, aiming to remain responsive to market demand and customer needs with limited resources (Poshdar et al. 2019). For example, SMEs adopt lean supply chain practices and JIT inventory management to minimise waste and enhance cost-effectiveness. Still, SMEs' main disadvantage to large companies is their limited resource availability, which constrains their capacity to invest in and integrate sophisticated digital technologies to minimise logistic waste (Kamble et al. 2018, Horváth & Szabó 2019). This limitation not only limits the acquisition of advanced algorithmic solutions but also restricts the implementation of necessary infrastructure for data handling and analytics, essential for running complex optimisation algorithms. In the end, these limitations stems from the lack of financial capability that is inherent to SMEs (Kiel et al. 2017). SMEs cannot fully capitalise on the benefits of automated and optimised supply chain systems without hardware and software to support these algorithms. Thus, it is crucial to have modifiable and robust algorithmic options.

Due to a lack of research and development (R&D) and training, SMEs' need for more necessary knowledge and skills significantly hinders their ability to deploy and manage complex algorithmic models (Stentoft et al. 2021, Masood & Sonntag 2020). Advanced supply chain algorithms often require specialised expertise in data science and algorithmic skills; these skills are typically scarce in smaller firms. The lack of technological expertise prevents SMEs from customising and optimising these algorithms to fit their specific operational constraints and scenarios, thus diminishing the potential efficiencies these tools could offer (Moeuf et al. 2020). An open-source algorithm framework becomes crucial to enable SMEs to modify and implement such technologies.

Effective use of supply chain optimisation algorithms involves more than just implementing technology; a strategic approach that aligns algorithmic deployment with overall business objectives is crucial. SMEs often struggle with strategic management that lacks a clear understanding of the implications of digitalisation (Liboni et al. 2019, Papulová et al. 2022, Matt et al. 2020). Without proper leadership to foresee the benefits and integrate these technologies into broader business practices, SMEs may not effectively leverage algorithms to streamline or improve supply chain operations (Heidemann Lassen & Waehrens 2021, Moldovan 2019).

These weaknesses directly affect SMEs' ability to optimise their supply chains. Despite their agility and flexibility, SMEs often need more robust supply chain frameworks that large corporations develop, essential for integrating global markets and managing complex production and distribution networks effectively. As a result, SMEs may need help implementing efficient, responsive, and sustainable supply chain strategies crucial in the sector's competitive market (Hansen et al. 2024, Buer et al. 2021, Di Bella et al. 2023). Additionally, SMEs' lack of quantifiable business metrics could pose a problem in effectively applying supply chain algorithms, as these are the foundational constraints.

SMEs and large companies increasingly incorporate value-driven metrics into their supply chain optimisation efforts, aligning operations with sustainability goals, customer satisfaction, and ethical purpose. In a survey conducted by Daugherty et al. (2021), approximately 60% of customers have prioritised value-driven metrics since 2021, sustainable in terms of work culture, environment and ethical practices. With 48% of companies say technology-led sustainability practices lead to increased revenues. This poses an advantage for SMEs as they often engage with local communities and adopt sustainable practices as unique selling points (USP) (Held et al. 2018). In contrast, large corporations pursue extensive sustainability programs and adhere to global certification standards.

In summary, the optimisation of supply chains in SMEs and large corporations is informed by differing capabilities, where SMEs have limited resources, knowledge and skills compared to large companies, where these are abundant. Thus, tailored strategies that recognise the unique circumstances of SMEs are essential for enabling them to achieve optimal supply chain efficiency and competitiveness in the evolving business landscape.

Aspect	**Key Insights**
Resource Availability	SMEs face significant limitations due to limited financial and technological resources, impacting their ability to invest in and integrate advanced digital technologies. Thus, adaptability and scalability is crucial.
Expertise and Skills	Lack of specialised expertise in data science and algorithmic skills in SMEs prevents the use and management of complex algorithmic models, necessitating open-source frameworks for easier adaptation.
Strategic Management and Operational Structure	SMEs often struggle with strategic management, lacking clarity in digitalisation's implications and failing to integrate technological advancements into broader business practices. Due to SMEs agile and flexible supply chain, responsiveness of technology is crucial.
Supply Chain Framework	SMEs typically lack robust supply chain frameworks that large corporations develop, limiting their ability to manage complex networks effectively.
Sustainability and Community Engagement	SMEs frequently utilise their local community ties and sustainability as USP, which can be advantageous compared to large corporations that must adhere to global standards.

Table 6: Summary of criteria for optimal supply chain optimisation in SMEs versus large corporations as discussed in Section 2.4 (Own Work)

2.5 Challenges and Possibilities for SMEs in Adapting and Adopting Algorithmic Models

Integrating algorithmic models into the supply chains of automotive SMEs presents a critical pathway to enhancing operational efficiency and market responsiveness. Despite the potential benefits, SMEs need help deploying these technologies primarily due to resource limitations identified in Chapter 2.4 and the need for scalable solutions addressed in Chapter 2.3. Algorithms such as the Non-dominated Sorting Genetic Algorithm (NSGA-II) have shown promise in addressing complex supply chain optimisation problems with less computational demand, making them suitable for SMEs, though this would depend on the number of supply chain objectives (Mekki et al. 2020, Deb et al. 2002). However, these models' broader adoption and effectiveness are limited by several barriers, including the accessibility of algorithmic frameworks, lack of implementation expertise, and the adaptability of models to SME-specific operational contexts (Kamble et al. 2018, Horváth & Szabó 2019, Stentoft et al. 2021). As most of these algorithm frameworks are targeted towards a specific aspect of the business, and its strategy for modified application is often ignored, these are addressed in the limitation of the methodology and future works of present papers (Sun & Su 2020, Li et al. 2019, Jokinen et al. 2015).

Comparative analyses indicate a disparity in the applicability of various algorithmic solutions, highlighting the lack of a one-size-fits-all model that caters to the diverse needs of SMEs. While specific algorithms may offer targeted benefits, such as transport route optimisation and inventory reduction, they often need to address the full spectrum of challenges faced by SMEs. The case studies from Sun & Su (2020), Li et al. (2019), Jokinen et al. (2015), Doganis et al. (2008), Khosroshahi et al. (2016), Luan et al. (2019), Rajak et al. (2022), Lv & Shen (2023), each focuses on a specific sector of optimisation, such as sustainability or inventory, but often ignore the broader metrics. This gap in the literature highlights the need for more nuanced and flexible algorithmic models. To effectively leverage the potential of algorithmic supply chain optimisation, SMEs require solutions that align theoretical innovation with practical operational needs. Future chapters should concentrate on adapting algorithms specifically tailored to SMEs' unique requirements. Improving SMEs' digital literacy and infrastructure is essential to ensure successful implementation.

In summary, algorithmic models offer significant opportunities for SMEs to optimise their supply chains while releasing these potential demands, overcoming numerous challenges related to adaptability and accessibility. The development of tailored, flexible solutions, alongside initiatives to build digital capabilities within SMEs, is essential for ensuring these enterprises survive the industrial transitions.

Challenge	**Insight and Opportunity**
Resource Limitations	SMEs face constraints in resources, which prevents the adoption of advanced algorithmic models. Enhancing digital knowledge and infrastructure could support better integration.
Lack of Scalable Solutions	Algorithms need to be adaptable to the specific needs of SMEs. Developing tailored solutions that align with SME operational realities is crucial.
Implementation Expertise	The absence of employee expertise to implement and manage sophisticated algorithms limits their effectiveness.
One-Size-Fits-All Models	Existing algorithms often do not cater to the diverse needs of SMEs. Promoting the development of flexible and modular algorithmic frameworks could provide more comprehensive benefits.
Practical Application of Theoretical Models	There is a disconnect between theoretical algorithmic innovations and their practical applications in SME settings. Future research should focus on adapting these models to real-world SME constraints.

Table 7: Summary of challenges and possibilities for SMEs in adapting and adopting algorithmic models as discussed in Section 2.5 (Own Work)

2.6 Gaps in Literature Review

The transition from Industry 4.0 to Industry 5.0 in the automotive sector signifies a promising horizon for enhancing efficiency and productivity, particularly for Small and Medium-sized Enterprises (SMEs). However, SMEs face substantial challenges in adapting and scaling algorithmic models for supply chain optimisation to these new industrial paradigms. The existing literature predominantly focuses on the application of these models within its broad usage, often neglecting the specific needs of SMEs and creating several notable knowledge gaps:

- **Adaptation and Scalability of Algorithmic Models for SMEs:** There is a lack of research focused on tailoring supply chain optimisation algorithmic models to the resource-constrained environments characteristic of SMEs.

- **Integration of Value-Driven Metrics in Algorithmic Models:** Current research insufficiently addresses the incorporation of value-driven metrics, such as environmental sustainability, employee well-being, and customer satisfaction—into algorithmic models for supply chain optimisation.

- **SME-Specific Industry 5.0 Transition Strategies and Human-Machine Collaboration:** The literature is limited on detailed strategies for SMEs applying Industry 4.0 technologies to Industry 5.0 human-centric approach, this value will be added by displaying how value-driven metrics can be integrated into optimisation algorithms.

In synthesising these gaps from the literature review conducted, it becomes evident that future research must focus on developing accessible, scalable, and value-aligned algorithmic supply chain optimisation models specifically designed for SMEs in the automotive industry. Such research should aim to bridge the divide between the potential of algorithmic optimisation and the practical realities faced by SMEs, ensuring that technological advancements of Industry 4.0 are leveraged to support sustainable, efficient, and human-centric supply chain operations inherent to Industry 5.0.

3 Methodology: A Multi-Layered Exploration

This chapter organises the methodology based on the Research Onion framework (Saunders et al. 2012), adapted to form Figure 8, systematically categorising each layer to highlight the philosophical underpinnings, research design, strategies, choices and techniques used to investigate the adaptation and scalability of algorithmic models for enhancing supply chain efficiency in SMEs amid their transition from Industry 4.0 to Industry 5.0.

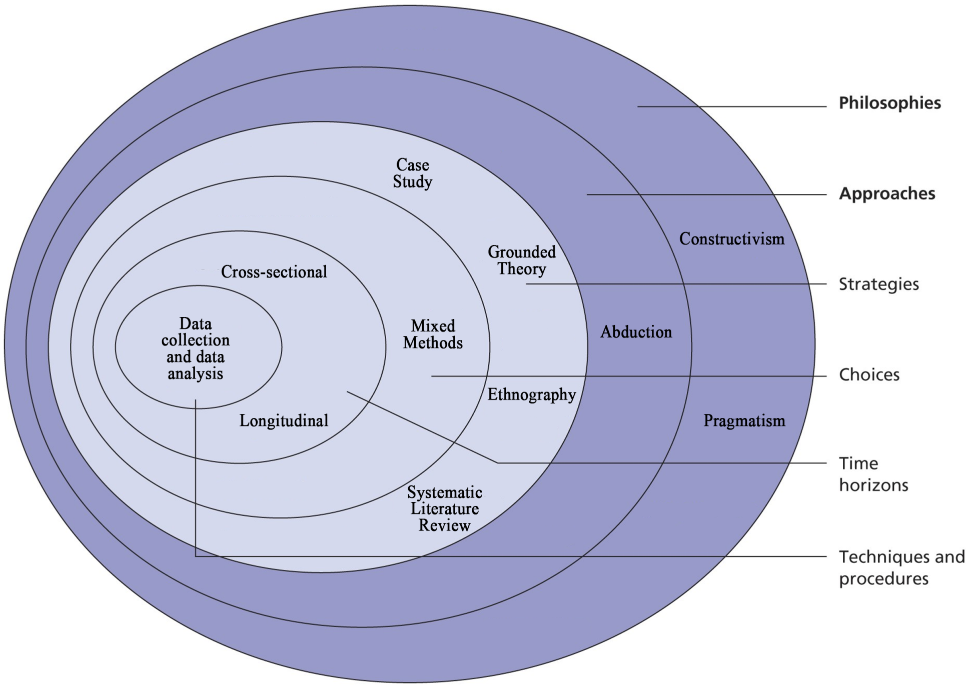


Figure 8: Research onion (Adapted from Saunders et al. (2012))

3.1 Philosophical Foundations

Pragmatism focuses on practical consequences, anything that would provide best position to answer the research question. It underlines the pursuit of practical supply chain algorithms that automotive SMEs can implement to navigate the transition from Industry 4.0 to 5.0. It allows greater flexibility in research method, integrating multiple analytical approaches and data types to address the multifaceted nature of supply chain optimisation.

Constructivism emphasises the importance of the subjective experiences and perspectives of automotive SMEs undergoing the industrial transition. It highlights that each SME constructs its knowledge and reality based on the environment, technology and individual internal capabilities. This study utilised constructivism to explore how SMEs perceive and adapt to changes, ensuring that the optimisation strategies are aligned with their unique challenges. It acknowledges that the researcher's synthesis of knowledge from diverse sources also forms a constructed understanding, which guides the criteria, selection and adaptation requirements of algorithm models for SMEs.

3.2 Research Approach

Abductive Approach aims to use known knowledge in order to generate further conclusions. It is chosen to facilitate an iterative cycle between knowledge derived from systematic literature review and empirical insights taken from secondary data analysis. This approach facilitates the generation of new theoretical insights and practical strategies by refining understandings based on present knowledge. It aligns with the research philosophy of pragmatism and constructivist insights into automotive SME-specific realities, enabling a dynamic adaptation of algorithmic models to suit present SME needs.

3.3 Research Strategies

Systematic Literature Review is conducted to collect, evaluate, and synthesise existing research on automotive SME needs and frameworks on supply chain optimisation. This approach ensures comprehensive coverage of the topic, identifying frameworks, methodologies, challenges, and gaps in existing body of knowledge. Aligning with the pragmatic philosophy of flexible research and allowing a constructivist approach of constructing knowledge based on present research.

Case Study Analysis provides an in-depth examination of specific instances of supply chain challenges within SMEs. It delves into documented instances where automotive SMEs have navigated the transition from Industry 4.0 to 5.0, leveraging algorithmic models, or fragmented parts of it. This method is invaluable for garnering qualitative insights into practical application of theories and identifying factors or criterias that influence the success and challenges of algorithms and implementation strategies.

3.4 Research Choices

Mixed Methods facilitates a nuanced exploration of supply chain optimisation combining quantitative data on algorithm performance and specific SME metrics with qualitative insights into

SME's experiences and strategies. This method, rooted in pragmatism, enables the study to produce comprehensive, practical outcomes that SMEs can realistically apply, informed by constructivist insights into their unique perspectives.

3.5 Time Horizons

Longitudinal Analysis tracing the historical evolution of supply chain optimisation algorithms and the shifts between industrial eras. This analysis offers a broader understanding of the progression and how past developments influence current automotive SME strategies, ensuring a deep contextual backdrop. Also allowing insights to matured and infant supply chain algorithms that are presently implemented. From Table 8 longitudinal covers 2010-2024.

Cross-Sectional Analysis providing focused insights into current practices and challenges, the paper employs cross-sectional analyses at two critical transitions: the latter phase of Industry 4.0 and the current state under Industry 5.0. This approach allows for an in-depth comparison of optimisation strategies, technological adoption, and automotive SME responses during these distinct periods, facilitating nuanced exploration of contemporary algorithm applications within SME supply chains. From Table 8 Industry 4.0 covers cross-sectional 2015-2019 and Industry 5.0 covers cross-sectional 2020-2024.

Year Range	Count	Details
Before 2010	6	Includes foundational works on JIT, foundational work on algorithms, and early discussions on knowledge management.
2010-2014	11	Focus on IoT, initial studies on Industry 4.0, and sustainability in supply chains, featuring significant advancements in automotive and supply chain management.
2015-2019	30	Growth in research on Industry 4.0, automotive industry focus, introduction of Industry 5.0 concepts, and sustainability practices in manufacturing.
2020-2024	45	Advanced discussions on Industry 5.0, sustainable practices in industry, technological innovations like NSGA-II and IoT, and increasing emphasis on smart manufacturing and resilience.

Table 8: Categorisation of References by Year Range for Time Horizons (Own Work)

3.6 Data Collection & Data Analysis

Data collection for this research will be multifaceted, utilising keywords from Table 10, primarily relying on comprehensive literature review complemented by the analysis of secondary data sources:

Literature Review: A systematic examination of academic articles, peer-reviewed journals, published journals, academic textbooks will be conducted. This review will focus on theoretical underpinnings, case studies, and the development of algorithmic theories related to supply chain optimisation within the automotive industry. Particularly focusing on identifying frameworks, methodologies, and outcomes of existing applications of algorithms in similar contexts, aiming to discern knowledge gaps, patterns and potential improvements.

Industry Reports: Automotive industry publications, reports and journals will be analysed to gain insights on current trends, challenges and advancements in supply chain optimisation technologies and practices within the automotive sector. This will provide a real-world perspective on the application and effectiveness of algorithmic models.

Category	Count	Details
Journal Articles	70	Focused on industrial engineering, supply chain management, optimisation algorithms, Industry transition, and Industry technologies. Publishers include IEEE, MDPI, Elsevier, Springer, Taylor & Francis, and Emerald.
Books	8	Guides and overviews such as "Quantitative methods in supply chain management: models and algorithms" by Christou, and academic textbooks on quantitative methods and research methodology.
Miscellaneous (Reports, Online Articles, etc.)	14	Includes WTO reports, European Commission reports, and articles from platforms like LinkedIn, as well as conference proceedings, master's theses, and technical reports.

Table 9: Categorisation of References by File Category from Data Collection (Own Work)

Key Topic/Keyword	Count
Industry 4.0	35
Sustainability	25
Algorithm (NSGA-II, PSO, MILP and etc.)	25
SME	23
Internet of Things (IoT)	20
Automotive Industry	18
Supply Chain Management	15
Industry 5.0	12
Smart Manufacturing	10
Lean Manufacturing	8
Artificial Intelligence	7
Customer Satisfaction	5

Table 10: Key Topics and Keywords Frequency in References (Own Work)

3.7 Algorithm Development and Discussion

1. **Design Principles:** Establish initial design criterias and choose a baseline algorithm based on the systematic literature review. Ensuring algorithm's suitability for SMEs, integration of Industry 4.0 technologies, and adherence to Industry 5.0 principles.

2. **Algorithm Structure:** A preliminary algorithm structure will be conceptualised, involving the adaptation of the chosen existing model, underlining adapation possibilities.

3. **Parameter and Objective Understanding:** Identify optimisation objectives specific to automotive SMEs. Establish parameters that will be chosen for optimisation. Adapt the existing model that is tailored for SMEs' supply chain optimisation needs. This involves detailing the algorithmic structure, operational logic, and incorporation of value-driven metrics, ensuring the algorithm is responsive to the shift towards Industry 5.0

4. **Tools and Rationale:** Python was selected for its comprehensive libraries like NumPy, Pandas, and DEAP, which support advanced data analysis and evolutionary algorithms. Python's versatility enhances the development of complex simulation models, important

for integrating various data and optimising algorithm performance in automotive SMEs. Its widespread use and extensive community allow reliable support.

5. **Simulation and Discussion:** Simulate the adapted algorithm to optimise the chosen objectives with the chosen parameters. Discuss simulation output and elaborate how it provides insight for automotive SMEs.

3.8 Methodology Limitation

This study acknowledges its inherent limitations, primarily the theoretical nature of its analysis and development of supply chain optimisation algorithms, attributed to the lack of actual automotive SME field testing. Acknowledgement is also made of the potential bias in interpreting sources for the literature review and the selection process of algorithms, which could influence research outcomes, especially due to pragmatic and constructivist philosophies and the abductive approach employed. Due to the academic nature of this study, time constraints are also acknowledged, which could influence data collection. Despite these constraints, the diversity of approaches and methodology adopted aims to mitigate these limitations, striving for a balanced and objective exploration of the research question. The methodologies were developed within the academic and practical boundaries to ensure the completion of the study while addressing its limitations.

4 Supply Chain Algorithms in The Automotive Industry

As the automotive industry navigates the transition from Industry 4.0 to Industry 5.0, SMEs face distinct challenges in optimising their supply chains. This chapter, informed by the literature review in Chapter 2, explore on a methodical selection of algorithms capable of enhancing supply chain efficiency within this sector. Evaluating a selection criteria framework to identify algorithms that excel in addressing complex, multi-objective optimisation problems relevant to SMEs in the automotive industry. An in-depth examination of each candidate algorithm will follow, evaluating their theoretical bases, industry applicability, and adaptability. Through a criteria-based evaluation process aiming to pinpoint the most effective algorithm for adaptation and implementation, aligning with the industry's shift towards sustainable and value-driven operations.

4.1 Algorithm Pool From Literature Review

Within the automotive industry's progression to Industry 5.0, SMEs seek adaptable and scalable supply chain optimisation algorithms. To progressively select which algorithm for adaptation, it would be prudent to roughly categorise them based on established criterias and literature insights from Chapter 2.3. The categorisation criteria considered will be, algorithm adaptability to SME supply chain requirements and algorithm computational and resource demand, which assumes higher resource demand means higher algorithm capability. From Figure 9, an adapted BCG matrix will be used as a foundational comparison framework (Morrison & Wensley 1991). Through the philosophical methodology of pragmatism multiple algorithms will be considered as long as it fits the requirements. Furthermore, constructivism allow for the placement of the algorithms in the matrix based on the case studies from Chapter 2.3.

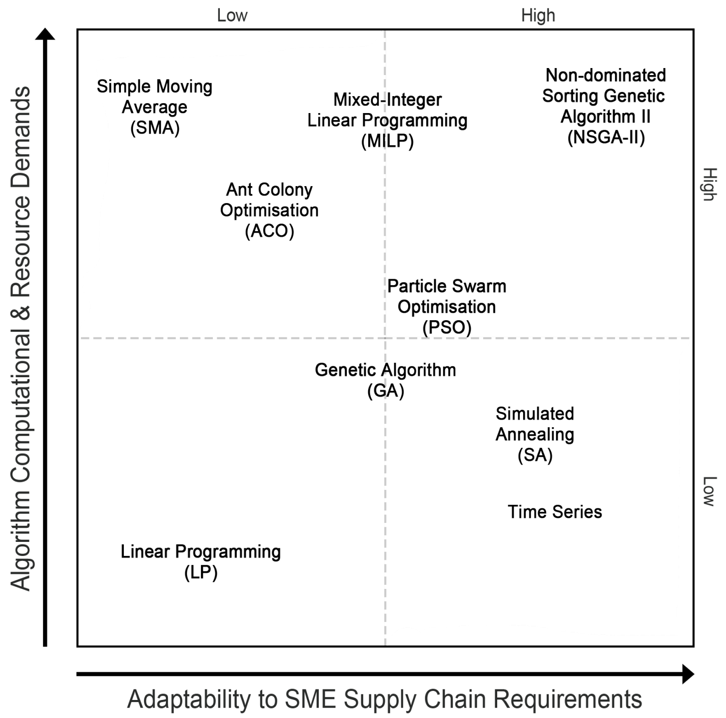


Figure 9: Matrix framework for algorithm comparison, adaptability to SME needs and resource demand, placement based on the case studies from Chapter 2.3 (Own work)

Three algorithms particularly standout in terms of SME adaptability and resource capability, which are NSGA-II, Particle Swarm Optimisation (PSO), and Mixed Integer Linear Programming (MILP). Further in-depth analysis will be conducted, to select one algorithm.

4.2 Evaluation of NSGA-II, PSO, and MILP

Based on matrix in Figure 9, three algorithms has been singled out as it provides high algorithm adaptability to SME supply chain requirements and algorithm computational and resource demand, which assumes higher resource demand means higher algorithm capability. The three algorithms are Non-dominated Sorting Genetic Algorithm II (NSGA-II), Particle Swarm Optimisation (PSO), and Mixed Integer Linear Programming (MILP)—have been selected for in-depth analysis. This subchapter will briefly introduce these potentially adaptable algorithms and provide advantages and disadvantages, which will further be dissected through the scoring table in the following subchapter.

4.2.1 NSGA-II (Non-dominated Sorting Genetic Algorithm II)

NSGA-II is an evolutionary algorithm designed for solving multi-objective optimisation problems, an improvement of its predecessor NSGA developed by Deb et al. (2002). NSGA-II operates through a process of selection, crossover, and mutation to generate a set of optimal solutions known as the Pareto front.

In supply chain optimisation, NSGA-II is utilised to address complex problems that involve multiple conflicting objectives, such as minimising costs while maximising service level (Sun & Su 2020). Its application extends to various aspects of the supply chain, from inventory management to distribution planning. The algorithm's advantages lies in its ability to find a diverse set of solutions and its applicability to real-world, dynamic problems, as discussed in automotive SMEs where resource allocation decisions are critical (Mekki et al. 2020, Kamble et al. 2018, Lv & Shen 2023). However, while it excels in identifying a broad set of potential solutions, its performance can be computationally intensive, and the quality of the solutions may depend on the choice of genetic operators and parameters (Sun & Su 2020, Babaveisi et al. 2018). Furthermore, as Bandyopadhyay & Bhattacharya (2014) argued, the algorithm may require careful calibration to align with the specific constraints and objectives of SMEs in the automotive industry. In conclusion, NSGA-II offers a robust framework for supply chain optimisation, balancing the trade-offs between multiple objectives.

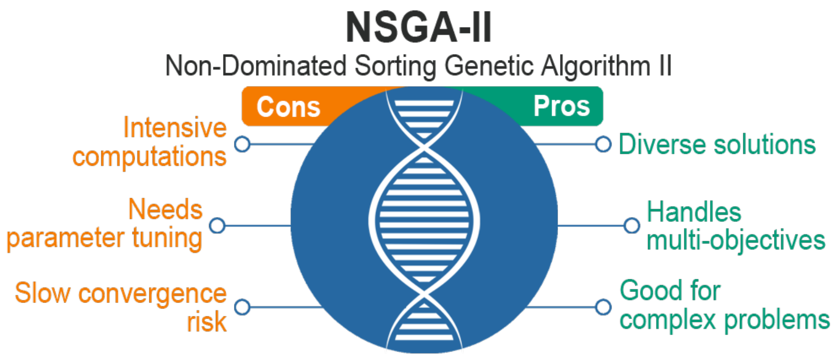


Figure 10: Highlighting the advantages and disadvantages of Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Own Work)

4.2.2 PSO (Particle Swarm Optimisation)

Particle Swarm Optimisation (PSO), developed by Kennedy & Eberhart (1995), is a computational method that optimises a problem by iteratively improving a individual solution with regard to a metric of quality. Inspired by the social behaviour of birds and fish, PSO optimises by having a population of candidate solutions, called particles, move through the solution space by following the current optimum particles.

PSO is suited for supply chain optimisation as it can handle various aspects like routing, inventory management, and logistics. Its effectiveness in the supply chain domain is due to its simplicity and efficiency in finding solutions quickly with few parameters to adjust, making it accessible for SMEs that may lack extensive computational resources (Kennedy & Eberhart 1995, Li et al. 2019). However, PSO can be prone to premature convergence and may require hybridisation with other algorithms to enhance its search capabilities for multi-objective problems found in supply chain optimisation. It also might need significant adaptation when dealing with discrete variables and constraints typical to supply chains (Soleimani & Kannan 2015). Despite these limitations, PSO remains a popular choice for supply chain problems in the automotive industry due to its versatility and ease of implementation.

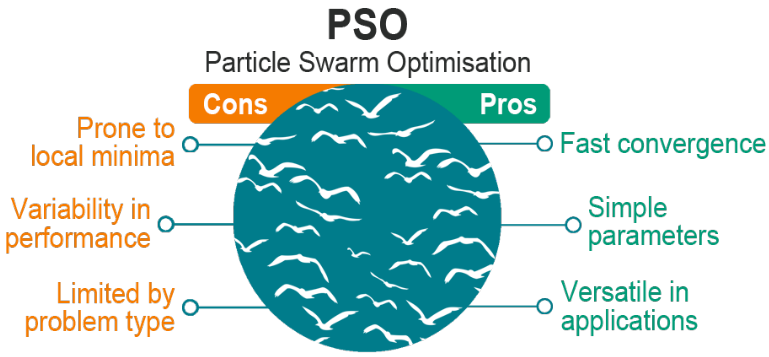


Figure 11: Highlighting the advantages and disadvantages of Particle Swarm Optimisation (PSO) (Own Work)

4.2.3 MILP (Mixed Integer Linear Programming)

Mixed Integer Linear Programming (MILP) is a mathematical optimisation approach that is derived from Linear Programming (LP), introduced in Beale & Small (1966). MILP functions by optimising a linear objective function, subject to a set of equations. This capability makes it highly suitable for supply chain optimisation, particularly in the automotive industry, where decisions about production, distribution, and resource allocation must adhere to strict constraints and operational guidelines (Qamar et al. 2020).

In supply chain applications, MILP is frequently used for optimising logistics networks, production location, and inventory management, offering precise solutions that is required by the SME. Its strengths include the precision of solutions and the ability to handle a wide range of operational constraints, providing clear insights for SMEs (Jokinen et al. 2015). However, the use of MILP can be computationally heavy, particularly for large-scale problems with many variables, which can be a limiting factor for SMEs with limited resources. Additionally, MILP models may require simplification to achieve computational useability, potentially reducing the quality of the solutions (Rajak et al. 2022).

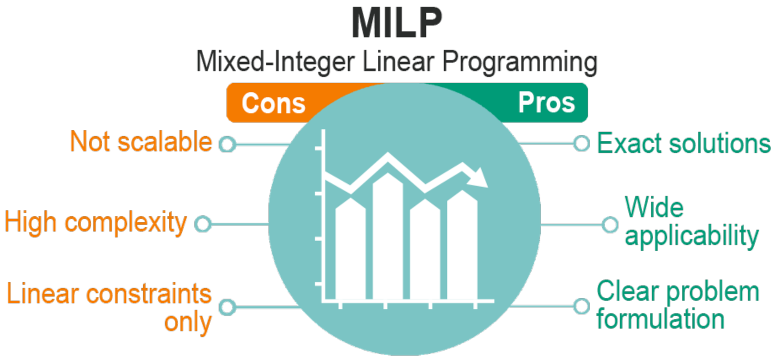


Figure 12: Highlighting the advantages and disadvantages of Mixed Integer Linear Programming (MILP) (Own Work)

4.3 In-depth Selection Criteria for Selected Algorithm

With a further understanding of the three chosen algorithms elaborated in, to optimise supply chain efficiency for SMEs within the context explored in Chapter 2, selecting an appropriate algorithm for adaptation is paramount. Through the consideration of SME criteria in Chapter 2.4 and adaptation challenges in Chapter 2.5, these selection criteria are synthesised. The subsequent analysis will employ these criteria to identify a suitable algorithmic model for further adaptation to SME needs. This approach ensures a methodical and objective selection process geared towards a sustainable, efficient, and technologically sound for SMEs in the automotive supply chain. These success criteria are given an essential factor; this provides different weighting for each criterion for the scoring table, categorised as low, medium and high importance, denoted by 1, 2, and 3, respectively..

Criterion	Importance Factor (Score)	Description	Rationale	Source
Computational Efficiency	Medium (2)	Measures the time an algorithm takes to provide a solution, convergence to solution.	Essential for real-time decision-making in dynamic supply chains.	(Mekki et al. 2020, Deb et al. 2002)
Scalability	Medium (2)	Evaluates the algorithm's ability to handle increasing volumes of data without performance degradation.	Crucial for growing SMEs. Possibility to scale up and down depending on SME scale.	(Hansen et al. 2024, Di Bella et al. 2023)
Accuracy	High (3)	Assesses the precision of the algorithm in producing correct results.	Vital for reliable supply chain management.	(Kamble et al. 2018, Horváth & Szabó 2019)
Resource Utilisation	Low (1)	Monitors the algorithm's consumption of computational resources.	Important for cost-effective implementation in SMEs.	(Kamble et al. 2018, Horváth & Szabó 2019)
Adaptability	High (3)	Rates how easily an algorithm can be tailored to specific industry needs, including integration with existing systems.	Critical to maintain algorithm effectiveness as industry conditions evolve.	(Kamble et al. 2018, Horváth & Szabó 2019)
Resilience	Medium (2)	Measures the algorithm's robustness and ability to recover from errors or disruptions.	A key factor in supply chain stability. Prevents disruptions in the agile supply chain of SMEs	(Kamble et al. 2018, Horváth & Szabó 2019)
Sustainability Integration	High (3)	Integration readiness with value-driven metrics	A critical factor to align Industry 4.0 technologies with Industry 5.0 human-centric values	(Wellbrock et al. 2020, Daugherty et al. 2021)

Table 11: Criteria for Evaluating Algorithm Performance with Importance Factors and Sources (Own Work)

4.4 Criteria Score Table

To ascertain the most suitable algorithm for adaptation to automotive SME supply chain needs, the criteria Table 11 will be utilised to evaluate the algorithms in Chapter 4.2. This table evaluates the algorithm through the case studies presented in Chapter 2.3 and the context in Chapter 4.2 against the criteria table; each algorithm will be given a performance factor depending on the suitability of each criterion. The performance factor is segmented into five: unsuitable, moderate, adequate, high, and optimal, denoted by 1 to 5, respectively. *[Note: All the criteria are evaluated in order low to high respectively, (e.g. high computational efficiency is optimal, thus, performance factor of 5) except for 'Resource Utilisation', as low resource utilisation is most optimal; thus, that will be denoted by 5]*

Selection criteria	**Importance Factor**	**NSGA-II**		**PSO**		**MILP**	
		PF	Score	PF	Score	PF	Score
Computational Efficiency	2	3	6	5	10	1	2
Scalability	2	5	10	3	6	3	6
Accuracy	3	4	12	4	12	5	15
Resource Utilisation	1	3	3	4	4	2	2
Adaptability	5	5	25	5	25	3	15
Resilience	3	5	15	3	9	2	6
Sustainability Integration	3	5	15	4	12	3	9
Total score		86		78		55	

Table 12: Score table for algorithm evaluation based on selection criteria Table 11 (Own Work)

Based on the score Table 12, NSGA-II emerges as the most appropraite algorithm for adaptation to automotive SME needs. Its strength in multi-objective optimisation aligns with the complex, variable-driven decisions required in SME supply chains. It particularly, excels in adaptability, resilience, and sustainability integration, according to the evaluative scoring Table 12 and established through the literature in (Deb et al. 2002, Sun & Su 2020). NSGA-II outperforms PSO and MILP when adapting to the multifaceted requirements of SME supply chains. Particularly, its high adaptability and scalability score reflects its flexibility in adjusting to the nuanced needs of SMEs, crucial in a industry driven by rapid technological evolution and the shift towards, more integrated, human-centric industrial practices.

Additionally, NSGA-II's strength in real-time processing makes it highly responsive to the dynamic supply chain demands, providing SMEs with strategic advantage in operational decision making. In contrast, PSO and MILP, while advantageous in their domainds, do not perform as uniformly across the spectrum of criterions, particularly in criterias of high importance to SMEs, such as resilience and capacity for sustainability integration. These attributes underscore NSGA-II's suitability further analysis and adaptation.

5 Understanding NSGA-II for Supply Chain Optimisation

This chapter marks the shift from conceptual exploration to the practical development of an algorithm specifically designed for supply chain optimisation in SMEs within the automotive industry. It will detail the theoretical and mathematical foundations of the NSGA-II algorithm, chosen from Chapter 4. This chapter sets the foundation for adaptation in the following chapters.

5.1 Theoretical Principles

NSGA-II, developed by Deb et al. (2002), operates on the principles of evolutionary algorithms, utilising mechanisms such as selection, crossover, and mutation to evolve a population of solutions towards the Pareto front. This front represents a set of non-dominated solutions, where no single solution can be considered superior to another without considering trade-offs between objectives. It evaluates individuals through the survival of the fittest. The algorithm employs four key processes illustrated in Figure 13:

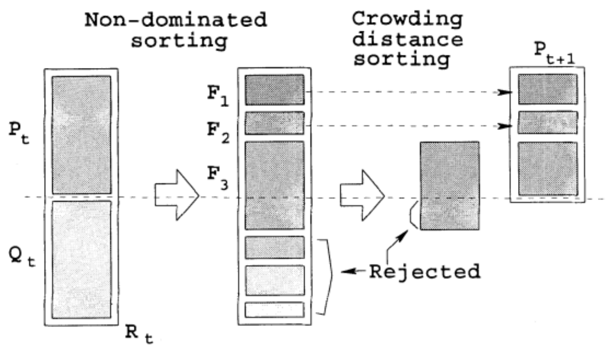


Figure 13: NSGA-II procedure, illustrating the algorithm's flowchart from initial population to the generation of a new population. (Taken from (Deb et al. 2002))

- **Fast Non-Dominated Sorting:** This step categorises the population into different levels based on dominance, ensuring diversity and convergence towards the Pareto front.
- **Crowding Distance:** A measure of the solution density surrounding an individual solution. It ensures a uniform spread along the Pareto front, preventing the clustering of solutions.
- **Selection:** NSGA-II utilises a fast non-dominated sorting approach to classify solutions based on dominance, assigning them into different fronts. Solutions in the first front are not dominated by any other; solutions in the second front are only dominated by those in

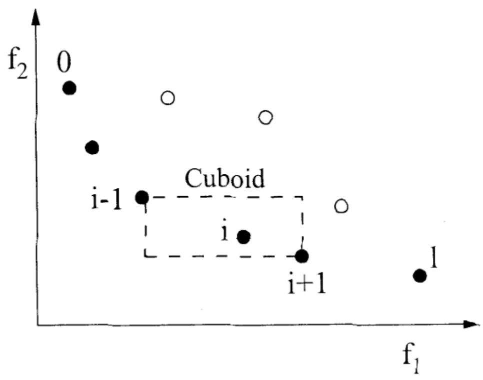


Figure 14: Crowding-distance calculation in NSGA-II. Points marked in filled circles are solutions of the same nondominated front. (Taken from (Deb et al. 2002))

the first, and so on. Dominated means one objective or more objective in that solution is better.

- **Crossover and Mutation:** These genetic operators generate new solutions by combining and altering parts of existing ones, introducing diversity and enabling the exploration of new areas of the solution space. Following the concept survival of the fittest Figure 13.

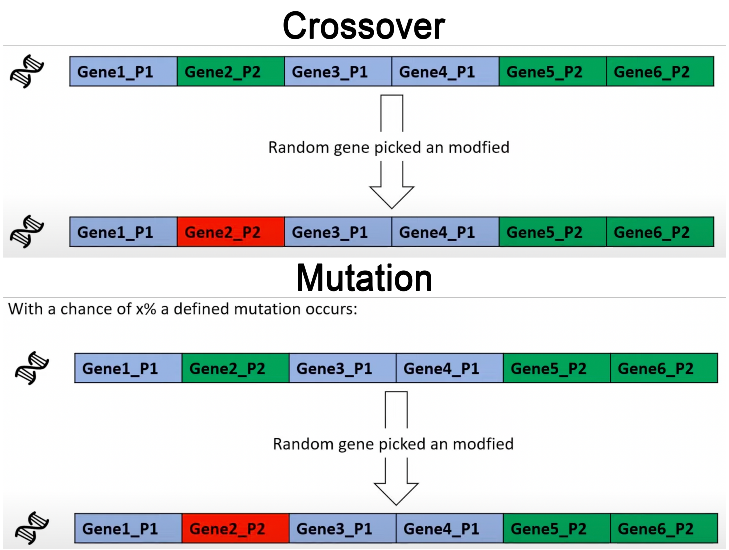


Figure 15: Crossover and mutation in NSGA-II. (Taken from (Paretos 2018))

The algorithm's focus on maintaining diversity, shown in Figure 14 alongside its sorting strategy, ensures a comprehensive exploration of potential solutions, making it highly effective for multi-objective optimisation tasks common in supply chain management, presenting a diverse solution, taking into account tradeoffs of objectives for SMEs to consider.

5.2 Mathematical Principles

The mathematical foundation of NSGA-II is rooted in the concepts of Pareto dominance, population genetics, and crowding distance (Deb et al. 2002).

Pareto Dominance is important to multi-objective optimisation and NSGA-II. A solution $\vec{\mathbf{x}}$ is said to dominate another solution $\vec{\mathbf{y}}$, if and only if, $\vec{\mathbf{x}}$ is no less optimal than $\vec{\mathbf{y}}$ for all objectives, and strictly better in at least one objective. Formally, for two solutions **x** and **y**, $\vec{\mathbf{x}}$ dominates $\vec{\mathbf{y}}$ (denoted as $\vec{\mathbf{x}} \succ \vec{\mathbf{y}}$) if:

$$\forall i \in \{1, 2, \ldots, n\}, f_i(\vec{\mathbf{x}}) \leq f_i(\vec{\mathbf{y}}) \tag{1}$$

$$\exists j \in \{1, 2, \ldots, n\}, f_j(\vec{\mathbf{x}}) < f_j(\vec{\mathbf{y}}) \tag{2}$$

Where f_i represents the i^{th} objective function to be either minimised or maximised.

In supply chain context, Pareto dominance is used to evaluate business possibilities based on conflicting objectives such as cost minimisation, environmental impact reduction, and customer satisfaction maximisation (Sun & Su 2020). Consider two hypothetical solutions, A and B, for a supply chain problem:

- Solution A: Low product cost, high environmental impact, high customer satisfaction
- Solution B: Higher product cost, lower environmental impact, slightly lower customer satisfaction

Solution A, lower costs and higher customer satisfaction but a greater environmental impact. Solution B, is more environmentally friendly but higher costs and slightly lower satisfaction. Neither solution Pareto dominates the other as each excels in different objectives. This scenario exemplifies the trade-off that NSGA-II presents in multi-objective optimisation producing a set of Pareto optimal solutions. SME Decision-makers can then select the most appropriate solution based on their priorities or further analysis balancing all objectives that are required.

Population and Fronts, at each iteration or generation, n, the algorithm maintains a population of potential solutions, denoted as P_t. The population is sorted into different fronts $F_1, F_2, \ldots, F_n$ based on non-dominance relations. The first front F_1, the Pareto front, contains solutions that are non-dominated by any other in the population. Each subsequent front F_i contains solutions only dominated by those in the previous fronts F_{i-1}.

In supply chain context, the first front, known as the Pareto optimal front, might include solutions that offer the best trade-offs between logistic costs and transport time, such as moderate logistic costs with reasonable delivery times, indicating neither is outperformed by others in all objectives. Subsequent fronts would organise solutions that are outperformed by those in the Pareto front but still represent possible objective strategies under certain conditions, like very low-cost options with longer delivery times. This sorting process helps identify a range of optimal and near-optimal solutions, assisting decision-maker in selecting supply chain strategies that best balance cost efficiency and delivery performance.

Crowding distance $d(i)$ measures the density of solutions around a particular solution i and is given by the sum of the normalised distances between the solution and its neighbors in the objective function space. It is computed for each solution on a particular front and is used as a secondary sorting criterion:

$$d(i) = \sum_{j=1}^{n} \left(\frac{f_j(i+1) - f_j(i-1)}{f_j^{max} - f_j^{min}} \right) \tag{3}$$

Where $f_j(i+1)$ and $f_j(i-1)$ are the objective function values of the solutions immediately preceding and succeeding i in the sorted list, and f_j^{max} and f_j^{min} are the maximum and minimum values of the objective function f_j in the entire population, respectively.

In supply chain context, crowding distance is a measure used to ensure diversity among the solutions, preventing the clustering of solutions and encouraging a uniform spread across the trade-off curve, allowing the business decision-makers a wide range of options. For example, if the objective within a supply chain is to reduce cost and environmental impact, it would do poorly if most solutions cluster around a particular cost range, it might limit the options available for decision-makers, especially if they seek solutions with a broader environmental impact range. This would greatly be reflected if there are numerous objectives. This encourages the algorithm to maintain diverse strategies within the population, such as some that favour cost reductions more heavily and other that prioritise environmental benefits, giving decision-makers a wide array of options to choose from that balance cost and sustainability in different ways.

Selection, Crossover, and Mutation operations are fundamental to NSGA-II's search process, shown in Figure 13. A binary tournament selection is performed based on the ranking and crowding distance, followed by genetic operators like crossover and mutation to generate a new population Q_t. The crossover operator combines pairs of solutions to produce offspring that inherit characteristics from both parents, while the mutation operator introduces random changes to individual solutions to maintain genetic diversity and explore new search areas.

In supply chain context, taking the previous scenario of minimising costs and environmental impacts, selection identifies promising supply chain strategies, such as those combining cost efficiency and low environmental impact, as parents for the next generation. Crossover then merges attributes of these selected parent strategies, for example, integrating one strategy's optimised logistic routes with another's eco-friendly shipping practices to create offspring that potentially outperform their parents in balancing economic and environmental objectives. Mutation further enriches the search by introducing random alterations, such as tweaking newly formed strategy's delivery network or substituting other environmental practices, thereby exploring new solution spaces that might uncover even more configurations. These processes collectively evolve the population toward diverse and optimised solutions continuously improving the trade-offs between minimising operational costs and reducing the supply chain's environmental footprint.

New Generation, the new population P_{T+1} for the next generation is formed by selecting the best solutions from the combined parent and child populations P_T and Q_T, based on their non-domination rank and crowding distance.

6 Strategic Application of NSGA-II in SME Supply Chain Optimisation

This chapter builds upon the foundational insights presented in previous chapters, particularly from Chapters 2, 4 and 5, which explored the domain of supply chain optimisation and algorithmic strategies within the automotive industry for SMEs. Drawing on the literature review in Chapter 2.2, which highlighted the specific requirements for supply chain optimisation in automotive SMEs, the operational capabilities of automotive SMEs in Chapter 2.4, and adaptation challenges in Chapter 2.5. These findings are hybridised with NSGA-II theories from Chapter 5. This chapter delves into practical applications and adaptations of the NSGA-II algorithm that SMEs can adopt.

6.1 Adapting NSGA-II for Automotive SME Operational Constraints

Through the literature review in Chapter 2.2 and 2.4, for automotive SMEs, supply chain optimisation must be adaptive, resource-efficient and scalable. Adapting NSGA-II to meet these constraints involves various aspects of the algorithm to tailor it to the limited resources and the need for flexible decision-making processes in SMEs.

6.1.1 Customising NSGA-II to SME Through Business Requirements

Objective Function Customisation for SMEs: For the optimisation objectives of NSGA-II, integrate specific business objectives inherent to SMEs, Chapter 2.2 and 2.4 like inventory turnover rate (e.g. product shortage, overstocking), cost reduction (e.g. logistics, manufacturing, procurement), and supplier performance (e.g. lead time, resilience) into the framework (Yildiz et al. 2016, Qamar et al. 2020, Dinsdale & Bennett 2015). This ensures the algorithm prioritises aspects critical to SME operational efficiency and profitability. For example, minimising the shortage of products (Z_1), illustrated in Eq(4) from (Babaveisi et al. 2018),

$$\text{Min } Z_1 = \sum_{\text{product}} \sum_{\text{period}} \left(\frac{\sum_{\text{vendor}} \text{Shortage of Product}}{\sum_{\text{vendor}} \text{Demand}} \right) \tag{4}$$

Incorporating SME Constraints into Algorithm Framework: Consider SME-specific constraints such as budget limitations, storage capacity, and minimum order quantities in the model;

this can be adjusted to fit the SME being considered (Poshdar et al. 2019, Yildiz et al. 2016, Qamar et al. 2020). This adaptation makes the algorithm's output values more practical and actionable, aligning with real-world operational boundaries SMEs face. For example, due to limited manufacturing capacity it would be prudent to set a product number limit for the algorithm, as this would affect other functions (e.g. revenue, cost, inventory), if there are two products it can be shown as, Eq(5),

$$\text{Production Limit} = [\text{Product } 1, \text{Product } 2] = [10000, 5000]\text{Units} \tag{5}$$

6.1.2 Customising NSGA-II to SME Through Algorithm Adjustments

Parameter Optimisation for SMEs: Adjust parameters like population size and mutation rates, that was discussed in Chapter 5.2, to find a balance that reflects the computational constraints of SMEs. For example, a smaller population size might be used to decrease computational load, crucial for businesses with limited IT infrastructure (Deb et al. 2002, Babaveisi et al. 2018).

Loop Integration: Incorporate feedback loops that allow for the real-time update of parameters based on ongoing inventory levels, demand forecasts, and supplier performance metrics (Deb et al. 2002, Hachem et al. 2021). This adjustment helps SMEs maintain resilience in the face of supply chain volatility, provides real-time decision making, aligning with the requirements discussed in Chapter 2.2 and 2.4.

Evolutionary Operators Customisation: Design custom crossover and mutation operators that consider SME-specific factors, as seen in Figure 15, such as lead times for sourcing from new suppliers or switching between JIT and JIC inventory strategies, providing a unique approach to exploring solutions (Deb et al. 2002). For example, in the case of inventory strategy, JIT or JIC, if α is crossover probability, a crossover outcome of two parents can be modelled as Eq(6),

$$\text{Child} = \alpha * \text{Parent1} + (1 - \alpha) * \text{Parent2} \tag{6}$$

Where α could adjusted based on the current variance in lead times in the supply chain. A higher variance in lead times might increase α, favoring strategies with higher safety stocks, JIC, while more stable conditions could decrease α, favoring JIT strategies.

Hierarchical Objective Optimisation: Implement a hierarchical approach that breaks down the supply chain optimisation objective into smaller, more manageable components like inventory management, transportation optimisation, and producer selection (Reichheld 2011, Yadav & Goel 2008). This structure allows SMEs to tackle complex problems segmentally, making the optimisation process less complex (Deb et al. 2002). This can be seen from Sun & Su (2020), where financial objectives are segmented from environmental objectives.

Real-time Data Integration: Enable NSGA-II to interface with enterprise resource planning (ERP) softwares for real-time data on sales, inventory levels, and supplier lead times, allowing the algorithm to adapt its optimisation strategies based on current operational data (Vu & Nguyen 2022, Deb et al. 2002).

SME-Focused Outputs: As the NSGA-II outputs a range of pareto optimal front solutions, prioritise solutions that offer quick wins in terms of cost savings and operational efficiency, crucial for SMEs needing to see immediate benefits from their optimisation efforts (Deb et al. 2002, Kamble et al. 2018, Qamar et al. 2020). This includes strategies that might offer incremental improvements in inventory accuracy or reduced logistics costs.

By adjusting NSGA-II around the unique operational characteristics of SMEs, the algorithm can become an essential tool for addressing the multifaceted challenges of supply chain optimisation in this sector. It is crucial that these changes maintain the balance between the algorithm's theoretical foundations and the practical realities of SMEs.

6.2 Integration of Industry 4.0 and 5.0 Technologies in NSGA-II

As established in Chapter 2.1, Industry 4.0 and 5.0 are continuous phases, with Industry 5.0 building upon the technological foundations of Industry 4.0 while incorporating a human-centric approach. This enables SMEs to leverage the advantages of big data analytics, IoT, and other cyber-physical systems while prioritising human-centric values and sustainable practices (Dirican 2015, Papulová et al. 2022, Breque et al. 2021, El Jaouhari et al. 2023). This subsection elaborates on how the interplay between technologies and human values can be incorporated into NSGA-II to increase SME decision-making and supply chain efficiency, with suggestions constructed from the knowledge of previous chapters and literature review.

Data-Driven Analytics and Human-centric Decision Making Integrating big data analytics into NSGA-II allows SMEs to process vast amounts of operational data and solutions for informed decision-making, aligning technological capabilities with human insights. By integrating real-time data streams from IoT, such as radio frequency identification (RFID) tags for product movement to manage inventory levels, NSGA-II can dynamically adjust to market demands and operational conditions, ensuring decisions are both data-informed, up-to-date and aligned with human worker's expertise and ethical considerations (Dirican 2015, Papulová et al. 2022).

Predictive Analytics, IoT, and Human Oversight: NSGA-II can utilise predictive analytics to enhance forecasting and optimise demand planning, while IoT sensors provide continuous data for real-time monitoring and adjustments (Hunke & Prause 2014). This interplay offers SMEs a proactive stance in managing their supply chains and ensures that human oversight guides the automated process, balancing efficiency with ethical responsibility. This allows for ease of use and reduces human interference as it addresses SMEs' limitations in workforce digital capability (Stentoft et al. 2021, Masood & Sonntag 2020).

Automated Processes and Human-Machine Collaboration: Through the application of NSGA-II, SMEs can automate their supply chain processes, ensuring efficient resource allocation and utilisation. Automation is guided by human decision-makers, setting appropriate constraining parameters; this ensures that operational practices reflect broader SME needs and sustainable values, emphasising customisation and sustainability (Breque et al. 2021, Xu, Lu, Vogel-Heuser & Wang 2021, El Jaouhari et al. 2023).

Here are three examples that illustrate the integration of NSGA-II with Industry 4.0 technologies and Industry 5.0 human-centric approach:

Inventory Management and Waste Sustainability: By integrating NSGA-II with IoT sensors such as RFID and optical sensors in warehouses, SMEs can manage inventory levels of automotive parts more precisely, minimising holding costs and reducing waste. This precision allows for adjustments in real-time as market conditions change, ensuring that sustainability is maintained through reduced inventory space and transportation fuel consumption (Saliji 2021, Lv & Shen 2023).

Predictive Maintenance and Ethical Practices: NSGA-II can be used for predictive optimisation of the supply chain. For example, based on Xu, Yang, Li, Gao, Wang & Ren (2021), NSGA-II can schedule maintenance of manufacturing equipment. By processing IoT data, the algorithm can predict when a machine is likely to fail and suggest preemptive maintenance schedules; this minimises downtime and supports ethical labour practices by ensuring workplace safety. Additionally, NSGA-II can also be used for predictive demand forecasting; it can adjust production amounts to align with demand requirements; not only does it minimise production costs of SMEs, but it also reduces product waste (Deb et al. 2002).

Route Optimisation: NSGA-II optimises delivery routes for logistics by processing real-time traffic data, delivery schedules, and warehouse-to-retailer distance. By utilising historical data and IoT data, the algorithm can dynamically reroute deliveries to avoid delays and reduce fuel consumption, demonstrating the adaptability required by SMEs during the transition to Industry 5.0, maintaining OTD and reducing fuel consumption (Sun & Su 2020, Zhang et al. 2003).

The integration of NSGA-II with Industry 4.0 technologies and 5.0 human-centric approach not only enhances the computational efficiency and data-driven capabilities of SMEs but also ensures that these technologies are applied in a manner that prioritises human interaction and sustainability. This also highlights the flexibility of NSGA-II in optimising various supply chain scenarios.

6.3 Integration to NSGA-II in a Framework

Figure 16 below provides an actionable example of the NSGA-II framework and its adaptation possibilities for SMEs. Synthesised through the considerations made in Chapter 6.1 and 6.2.

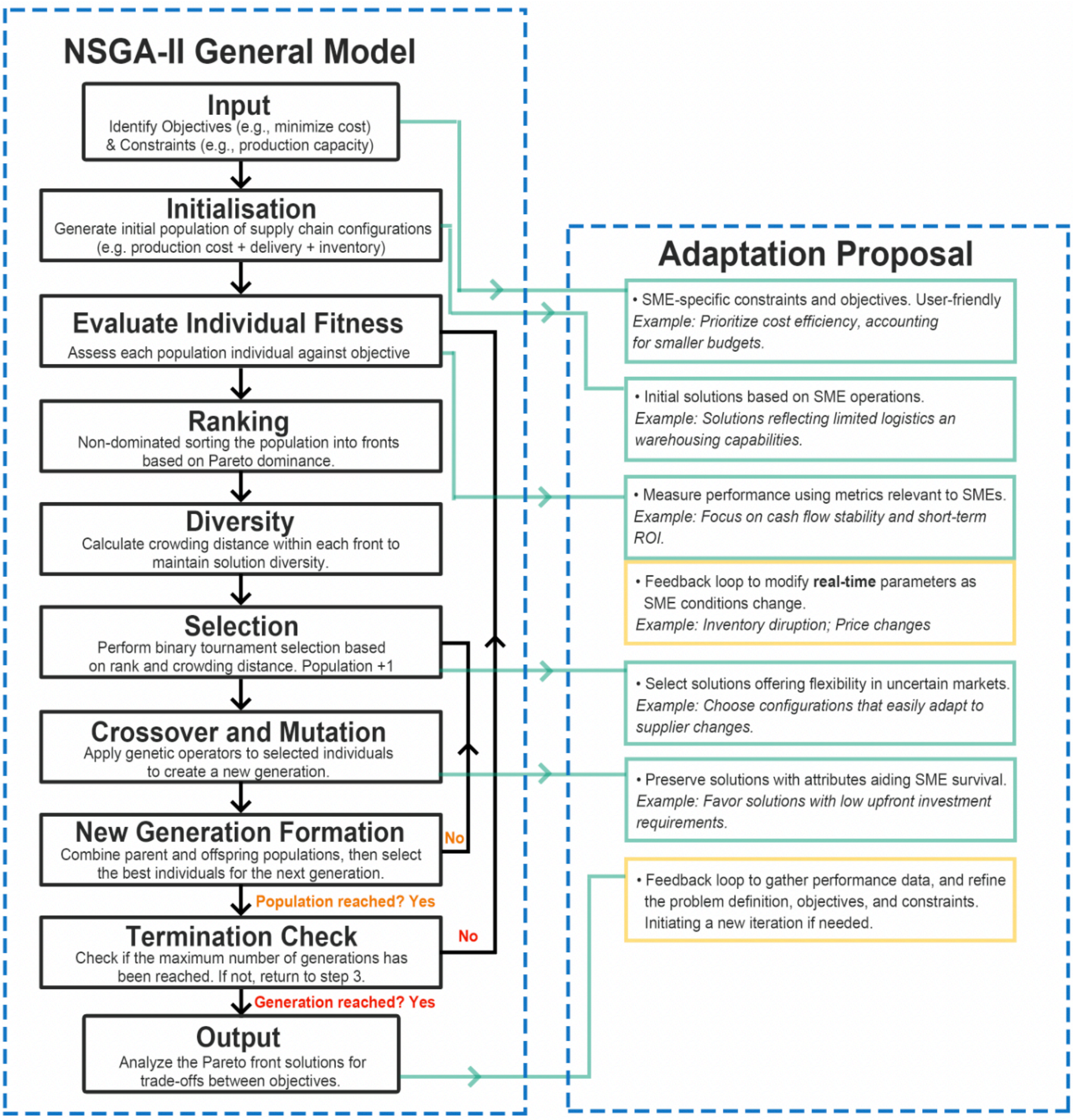


Figure 16: Example of NSGA-II framework, displaying its general model as a flowchart and adaptation proposal (Own Work)

Figure 16 focuses on tailoring a value-driven algorithm that not only satisfies SME objectives but also adheres to the parameter constraints of SMEs. The subsequent work is on developing the algorithm in Python code to simulate the practicality in real-world supply chain problems, bridging theoretical research and practical outputs.

7 Framework Implementation and Adoption Parameters

This chapter, through the considerations done in Chapter 2, 5, and 6, aims to provide SMEs with a pragmatic walkthrough utilising the framework in Figure 16 to tackle their multifaceted challenges. By illustrating how to clearly define the objective functions and parameters relevant to SME supply chains, this example serves as a blueprint for SMEs to enhance their operationality and competitiveness in the ever-evolving industry. This example addresses the customisation possibilities from the literature review and elaborates on how SMEs can alter the framework to suit their unique situations. This chapter covers setting up an NSGA-II algorithm in Python through the DEAP library.

7.1 Problem Definition and Assumptions

In this example, consider an SME automotive parts retailer, which sources various parts from multiple manufacturers, stores it in a network of storage centres before distributing directly to customers through their retail store. This can be illustrated through a forward logistics network that includes 2 manufacturers, 2 storage centres, 1 retailer, and customers.

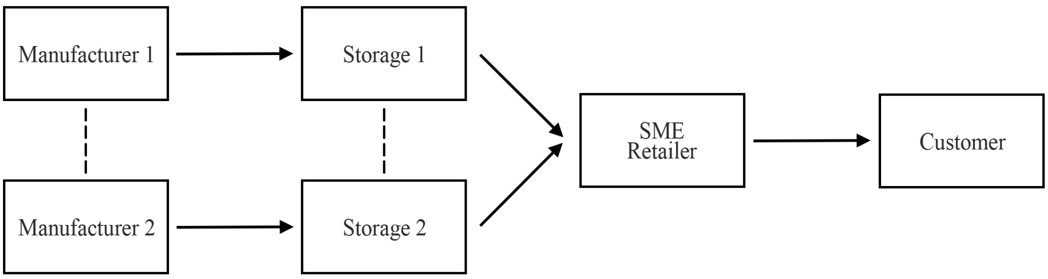


Figure 17: Forward supply chain logistic network scenario (Own Work)

Establishing the objective functions of the NSGA-II algorithm from the retailer's perspective, particularly for a single SME retailer. This concentration aligns with the retailer's pivotal role in direct customer interactions, production scales, inventory management, revenue consideration and the delivery process, areas crucial for optimisation to enhance operational efficiency, competitiveness, and customer satisfaction. This approach is tailored to the realities of SMEs in the supply chain, making the research directly applicable to real-world scenarios and providing a focused yet comprehensive exploration of supply chain optimisation.

The main objectives being addressed in this example are to find the optimal strategy to increase revenue, customer satisfaction, and delivery rates, while reducing environmental impact, operational costs, and quality control, objectives that are considered as SME priorities made in the literature review Chapter 2, (Kamble et al. 2018, Horváth & Szabó 2019, Hachem et al. 2021, Zhang et al. 2003, Yildiz et al. 2016, Rožanec et al. 2021, Qamar et al. 2020, Aghazadeh 2003, Saliji 2021, Dinsdale & Bennett 2015). Hence, a multi-objective optimisation model is formulated. The first objective is to maximise total revenue. The second objective is to minimise operational costs, which cover production, transportation and inventory costs. The third objective is to minimise quality control costs. The fourth objective is to minimise environmental impact. The fifth objective is to maximise delivery rates through on-time delivery (OTD) rates. The sixth objective is to maximise customer satisfaction through NPS of customer OTD. Lastly, the seventh objective is to maximise customer satisfaction through NPS of customer environmental satisfaction

The assumptions and limitations of the model are as follows.

1. No product flows exist between facilities of the same category (e.g. no product transfer from storage 1 to 2)

2. The locations of manufacturing plants and distribution centres are determined (e.g. distances are fixed)

3. Single flow forward logistics, assuming that products flow in a single direction from manufacturers to storages to the retailer without any reverse logistics or recycling processes included

4. Technological uniformity, assuming that all facilities are equipped with similar technology levels for production and inventory management, which affects efficiency and operational costs

5. Products moved from storage to retailer are considered sold, for revenue calculation

7.2 Defining Indices of The Problem

Four types of indices are considered in this paper:

- i: index of products, $i \in I$;
- m: index of manufacturing centres (manufacturers), $m \in M$;

- s: index of storage centres, $s \in S$;
- r: index of automotive SME retailer.

7.3 Defining Parameter Variables of The Problem

Symbol	Description
Z_x	Objective function x
$q_{s,i}$	Quantities of product i from storage s to retailer r
$q_{m,i}$	Quantities of product i from manufacturer m to retailer r
n	Number of different products
P_i	Selling price per unit at the retailer for product i
$C_{\text{prod},i,m}$	Production cost for product i at Manufacturer m
$C_{\text{inv},i,m}$	Inventory holding cost per unit for product i at Storage j
$C_{\text{qc},i}$	Quality control cost per unit for product i
$p_{\text{def},i}$	Probability of defects for product i
C_{trans}	Transport cost per unit per kilometer
E_{unit}	Environmental impact per unit per kilometer
D_i	Expected demand for product i at the retailer
$d_{m,s}$	Distance from Manufacturer m to Storage s
$d_{s,r}$	Distance from Storage s to the Retailer r
E	Environmental impact factor per unit per kilometer
r_{fuel}	Fuel consumption rate (liters per kilometer)
C_{fuel}	Cost of fuel per liter
C_{veh}	Vehicle capacity (units)
L	Load factor (percentage utilisation of vehicle capacity)
F	Emission factor (kg CO2 per liter of fuel)

Table 13: Parameter Definitions for NSGA-II Optimisation Model (Own Work)

7.4 Mathematical Model: Modelling Product Demand and Objective Functions

This supply chain scenario can be modelled and optimised through the NSGA-II algorithm, accounting for the complexities inherent in a multi-tiered distribution network and embracing market demand's unpredictability. This subchapter will detail the construction of a multi-objective optimisation framework using the NSGA-II algorithm, focusing on the seven objective functions. Each function targets a specific aspect of the supply chain's performance, ensuring that the model comprehensively addresses the unique priorities of an automotive SME.

Modelling Product Demand

Central to our algorithm model is the prediction of product demand, which serves as the foundational input for all optimisation related to customer product demand. In real-life scenarios, demand is inherently uncertain and subject to fluctuations influenced by market trends, consumer behaviour, and economic factors. To realistically model this uncertainty, from an economics book by Ross (2014), demand for each product at the retailer can be modelled as,

$$P(D_i \leq x) = \int_0^x f_{D_i}(t)\, dt \tag{7}$$

For simulation, demand D_i is considered a random variable modelled by the probability density function (PDF), randomised by product quantity mean and standard deviation estimated based on historical SME product demand data, allowing the model to adapt to inherent market volatility. This approach acknowledges the unpredictability in demand, enabling the supply chain to be optimised against a range of possible future scenarios rather than a single, possibly inaccurate, forecast.

Maximising Revenue Z_1

$$\text{MAX } Z_1 = \sum_{i=1}^{n} \sum_{s=1}^{2} (q_{s,i} \times P_i) \tag{8}$$

Where $q_{\mathrm{s},i}$ represent the quantities of product i transported from Storage s to the retailer, and P_i is the selling price per unit of product i (Atrill & McLaney 2008). For revenue, when product is moved from storage s to retailer r it is considered sold.

Minimising Total Cost Z_2

Total cost is the sum of production, transport, and inventory costs (Atrill & McLaney 2008):

$$\text{MIN } Z_2 = \text{Production Cost} + \text{Transport Cost} + \text{Inventory Cost} \tag{9}$$

Production Cost

$$\text{Production Cost} = \sum_{i=1}^{n} \sum_{m=1}^{2} q_{m,i} \times C_{\text{prod},i,m} \tag{10}$$

Where $q_{\mathrm{m},i}$ represent the quantities of product i produced by Manufacturer m, respectively, and

$C_{\text{prod},i,m}$ is the production cost per unit of product i at Manufacturer m.

Transport Cost

$$\text{Transport Cost} = \sum_{i=1}^{n} \left(\sum_{m=1}^{2} q_{m,i} \times C_{\text{trans}} \times d_{m,s} + \sum_{s=1}^{2} q_{s,i} \times C_{\text{trans}} \times d_{s,r} \right) \tag{11}$$

Transport cost considers the distances from manufacturers m to storages s and from storages s to the retailer r.

Inventory Cost

$$\text{Inventory Cost} = \sum_{i=1}^{n} \sum_{s=1}^{2} q_{s,i} \times C_{\text{inv},i,s} \tag{12}$$

Where $q_{\text{s},i}$ represent the quantities of product i transported from Storage s to the retailer s, and $C_{\text{inv},i,s}$ is cost per unit of product i at Storage s

Quality Control Cost Z_3

$$\text{MIN } Z_3 = \sum_{i=1}^{n} (q_{\text{total},i} \times C_{\text{qc},i}) \tag{13}$$

Where $q_{\text{total},i}$ is the total quantity of product i handled across the entire supply chain. Modelled through insights from Mehrdad Mohammadi & Tavakkoli-Moghaddam (2015) and Xu, Yang, Li, Gao, Wang & Ren (2021).

Environmental Impact Z_4

$$\text{MIN } Z_4 = \sum_{i=1}^{n} \sum_{m=1}^{2} q_{m,i} \times E_{\text{unit}} \times (d_{m,s(m)} + d_{s(m),r}) \tag{14}$$

Calculated based on the total distance travelled by each product from manufacturers through storage to the retailer. Where $q_{m,i}$ is the total quantity of product manufactured from m, as the established in Figure 17, correspondence between manufacturers and storages is fixed, such that each manufacturer m has designated storage s, $s(m)$ denotes as corresponding storage s to the manufacturer m (e.g. Manufacturer 1 transport only to Storage 1). Modelled by insights from Sun & Su (2020) and Ross (2020).

On-Time Delivery (OTD) Z_5

$$\text{MAX } Z_5 = -\sum_{i=1}^{n} \left(\max(0, D_i - \sum_{s=1}^{2} q_{s,i}) \right)^2 \tag{15}$$

Measures deviations from the product demand—how short product deliveries to retailers are compared to what was actually required. Calculated by $D_i - \sum_{s=1}^{S} q_{s,i}$. The $\max(0, x)$ function ensures that it only considers situations where there is a shortage ($D_i > \sum_{s=1}^{S} q_{s,i}$). If the delivery quantity meets or exceeds demand, the result of the max function is zero, thus no penalty. The negative sign before the summation transforms penalties for shortages into a value to be maximised, allowing the use of minimisation algorithms. Shortages are quantified by $\max(0, D_i - \sum_{s=1}^{S} q_{s,i})$ and squared to penalise larger discrepancies. This equation focuses on minimising the negative of the penalties. Modelled by insights from Deb et al. (2002), Memari et al. (2017), and Lv & Shen (2023).

NPS for OTD Z_6

$$\text{MAX } Z_6 = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{\min\left(\sum_{s=1}^{2} (q_{s,i}), D_i\right)}{D_i} \right) \tag{16}$$

Reflects customer satisfaction potential by calculating the average ratio of the delivered quantity that meets or exceeds the demand across all products Memari et al. (2017) and Lv & Shen (2023).

NPS for Environmental Impact Z_7

$$\text{MAX } Z_7 = 1 - \left(\frac{\text{Environmental Impact}}{\text{Max Environmental Impact}} \right) \tag{17}$$

Designed to evaluate the environmental efficiency of the supply chain operations. It is defined by the equation: Where:

- **Environmental Impact** measures the environmental impact by the supply chain activities.
- **Max Environmental Impact** is the theoretical maximum impact under regulation determined by scenarios of maximal operational intensity and inefficiency.

A higher value of Z_7 indicates better environmental performance, demonstrating a lower actual impact relative to the possible maximum. This inverse relationship aligns with sustainability objectives, rewarding lower environmental impacts with higher scores.

7.5 Establishing Algorithm Parameter Values

This chapter outlines the parameter values of the variables in Chapter 7.3 and is used in the NSGA-II algorithm objective function in Chapter 7.4 for optimising an automotive SME supply chain, justified by SME constraints. The parameters are organised by their relevance to specific operational aspects such as demand forecasting, revenue generation, and cost management.

Demand Parameters

Mean Demands (μ) and Standard Deviations (σ):

$$\mu_i = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} = \begin{bmatrix} 1000 \\ 800 \\ 600 \end{bmatrix} \text{ unit}, \quad \sigma_i = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \end{bmatrix} = \begin{bmatrix} 200 \\ 180 \\ 160 \end{bmatrix} \text{ unit}$$

The mean demands represent the expected sales per product i, adjusted based on historical SME data. The standard deviations reflect the variance in product i demand D_i. This random modelling, forecasts demand D_i as a value of uncertainty.

Revenue Parameters

Selling Price by SME Retailer (P_i):

$$P_i = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} = \begin{bmatrix} 15 \\ 18 \\ 25 \end{bmatrix} \text{ GBP/unit}$$

These values are set to simulate an SME part sold by the retailer.

Cost Parameters

Production Costs ($C_{\text{prod},i,m}$):

$$C_{\text{prod},i,m} = \begin{bmatrix} C_{\text{prod},1,1} & C_{\text{prod},2,1} & C_{\text{prod},3,1} \\ C_{\text{prod},1,2} & C_{\text{prod},2,2} & C_{\text{prod},3,2} \end{bmatrix} = \begin{bmatrix} 10 & 15 & 20 \\ 11 & 14 & 22 \end{bmatrix} \text{ GBP/unit}$$

Inventory Costs Per Unit Product at Storage ($C_{\text{inv},i,m}$):

$$C_{\text{inv},i,m} = \begin{bmatrix} C_{\text{inv},1,1} & C_{\text{inv},2,1} & C_{\text{inv},3,1} \\ C_{\text{inv},1,2} & C_{\text{inv},2,2} & C_{\text{inv},3,2} \end{bmatrix} = \begin{bmatrix} 0.2 & 0.3 & 0.3 \\ 0.2 & 0.3 & 0.2 \end{bmatrix} \text{ GBP/unit}$$

Quality Control Costs Per Unit Product ($C_{\text{qc},i}$):

$$C_{\text{qc},i} = \begin{bmatrix} C_{\text{qc},1} \\ C_{\text{qc},2} \\ C_{\text{qc},3} \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.4 \\ 0.5 \end{bmatrix} \text{ GBP/unit}$$

Defect Probability ($p_{\text{def},i}$):

$$p_{\text{def},i} = \begin{bmatrix} p_{\text{def},1} \\ p_{\text{def},2} \\ p_{\text{def},3} \end{bmatrix} = \begin{bmatrix} 0.1 \\ 0.07 \\ 0.05 \end{bmatrix}$$

These costs represent the expenses related to production, inventory, and quality control defects. They are critical for managing operational costs and ensuring product quality.

Transport Parameters

Transport Cost Per Unit Per Km (C_{trans}):

$$C_{\text{trans}} = \begin{bmatrix} 0.00346 \end{bmatrix} \text{ GBP/km}$$

Calculated using the following formula. It quantifies the parameters of a typical freight truck based on present data. Fuel consumption r_{fuel} , 0.35 litres/km (FreightWaves 2019). Fuel cost of diesel C_{fuel}, 1.58 GBP/litre (RAC 2024). Theoretical vehicle capacity considering product size C_{veh}, 200 Units (Assuming product i are all of similar dimensions and mass). Load factor

L, 0.8.

$$\text{Transport Cost per Unit per Km} = \frac{r_{\text{fuel}} \times C_{\text{fuel}}}{C_{\text{veh}} \times L} = \frac{0.35 \times 1.58}{200 \times 0.8} \tag{18}$$

Environmental Impact Parameters

Emission Factor (E) (Ross 2020):

$$E = \begin{bmatrix} 2.68 \end{bmatrix} \text{ kg CO2e/liter}$$

Environmental Impact Per Unit Per Km (E_{unit}):

$$E_{\text{unit}} = \begin{bmatrix} 0.0058625 \end{bmatrix}$$

Calculate using the following formula. It quantifies the environmental impact per kilometer traveled.

$$\text{Environmental Impact per Unit per Km} = \frac{r_{\text{fuel}} \times E}{C_{\text{veh}} \times L} = \frac{0.35 \times 2.68}{200 \times 0.8} \tag{19}$$

Max Environmental Impact:

$$\text{Max Environmental Impact} = \begin{bmatrix} 1.5 \end{bmatrix}$$

Distances From Manufacturer to Storage ($d_{m,s}$):

$$d = \begin{bmatrix} d_{1,1} & d_{2,2} \end{bmatrix} = \begin{bmatrix} 100 & 100 \end{bmatrix} \text{ km}$$

Distances From Storage to Retailer ($d_{s,r}$):

$$d = \begin{bmatrix} d_{s,r} & d_{s,r} \end{bmatrix} = \begin{bmatrix} 50 & 50 \end{bmatrix} \text{ km}$$

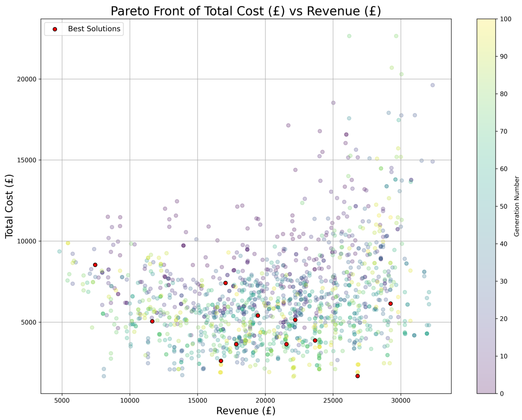
7.6 Results: Simulated Algorithm Output

No.	Revenue (£)	Total Cost (£)	QC Cost (£)	EV Impact	OTD	NPS OTD	NPS EV
1	26,815	1,685.842	585.7	70.35	-1.781×10^8	0.060	-45.9
2	16,719	2,619.543	412.6	139.82	-1.833×10^8	0.038	-92.2
3	29,244	6,149.964	747.3	339.44	-1.769×10^8	0.066	-225.3
4	21,558	3,650.585	539.8	207.53	-1.810×10^8	0.049	-137.4
5	23,667	3,878.086	579.2	211.93	-1.815×10^8	0.053	-140.3
6	7,444	8,541.175	359.3	426.50	-1.932×10^8	0.017	-283.3
7	17,857	3,651.452	448.6	170.60	-1.849×10^8	0.040	-112.7
8	11,655	5,053.541	369.7	294.59	-1.891×10^8	0.026	-195.4
9	17,057	7,422.091	531.6	365.82	-1.845×10^8	0.038	-242.9
10	19,444	5,413.535	525.3	267.33	-1.846×10^8	0.044	-177.2
11	22,207	5,144.620	585.4	290.19	-1.811×10^8	0.050	-192.5
Average	19,424.273	4,837.312	516.773	253.100	-1.835×10^8	0.044	-162.714

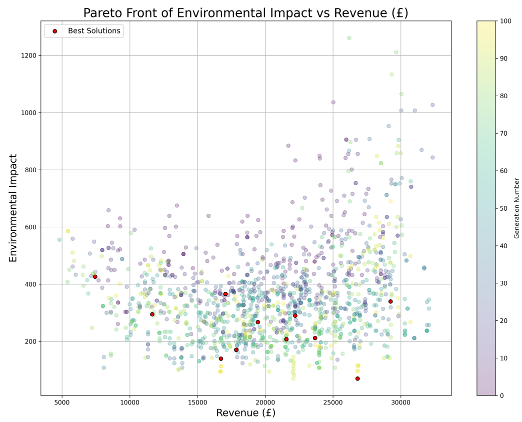
Table 14: Key financial and environmental metrics of best solutions, simulated NSGA-II algorithm output (Own Work)

	Revenue : Total Cost : EV Impact	Revenue/Total Cost
1	381.17 : 23.96 : 1.0	15.91
2	119.58 : 18.74 : 1.0	6.38
3	86.15 : 18.12 : 1.0	4.76
4	103.88 : 17.59 : 1.0	5.91
5	111.67 : 18.30 : 1.0	6.10
6	17.45 : 20.03 : 1.0	0.87
7	104.67 : 21.40 : 1.0	4.89
8	39.56 : 17.15 : 1.0	2.31
9	46.63 : 20.29 : 1.0	2.30
10	72.73 : 20.25 : 1.0	3.59
11	76.53 : 17.73 : 1.0	4.32
Average	105.90 : 19.10 : 1.0	5.00

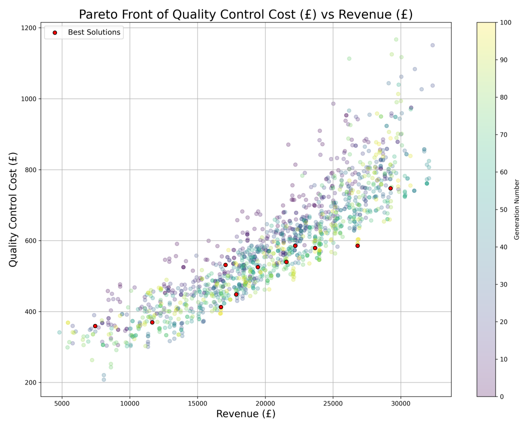
Table 15: Revenue efficiency and environmental impact ratios, including NPS OTD to NPS EV ratio, simulated NSGA-II algorithm output (Own Work)



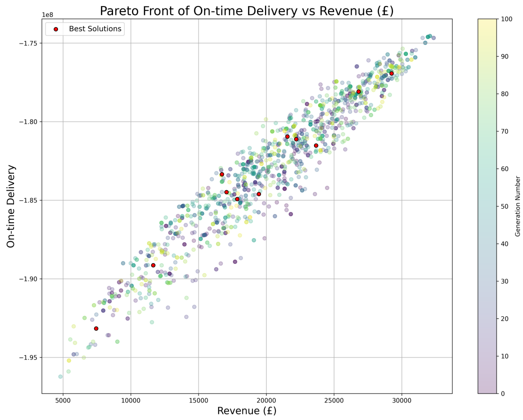
(a) Total Cost (GBP) vs Revenue (GBP)



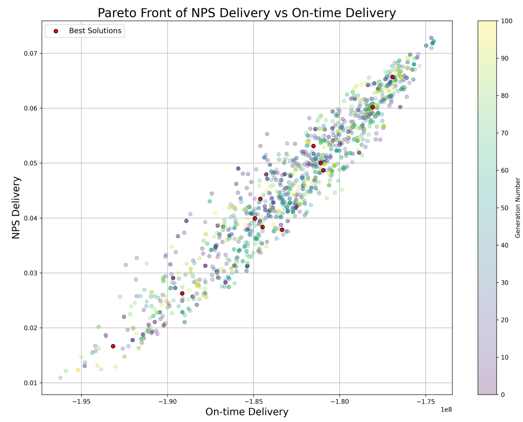
(b) Environmental Impact vs Revenue (GBP)



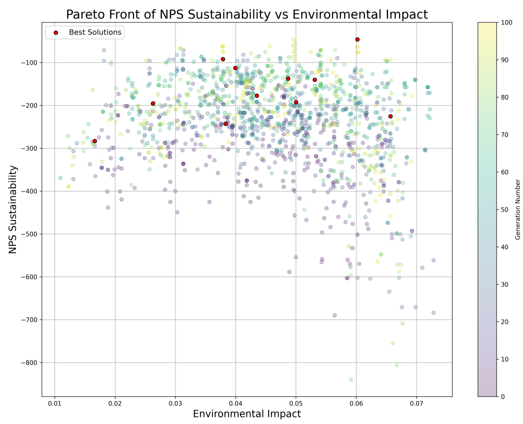
(c) Quality Control (GBP) vs Revenue (GBP)



(d) On-time Deliveries vs Revenue (GBP)

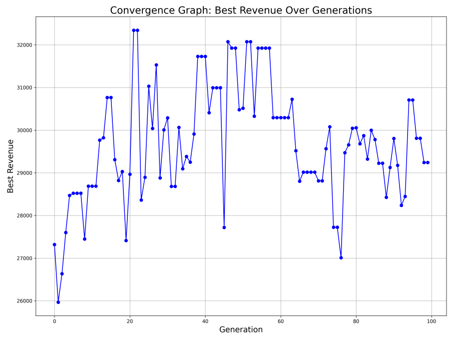


(e) NPS Delivery vs On-time Deliveries

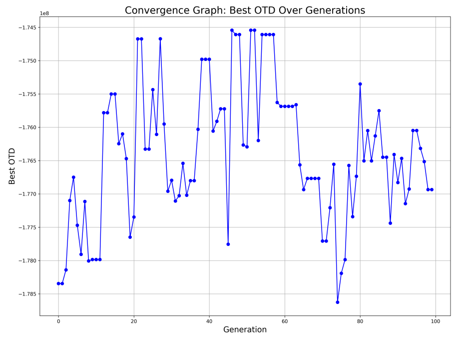


(f) NPS Sustainability vs Environmental Impact

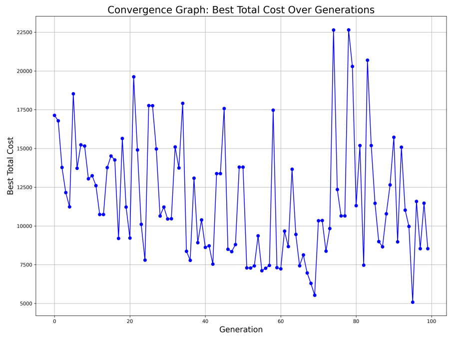
Figure 18: Pareto front graphs illustrating the trade-offs between two objective functions. *[Note: Each subplot represents a unique scenario, the 'best solutions' highlight the optimal solutions where no further improvements can be made in one objective without sacrificing the other.] (Own Work)*



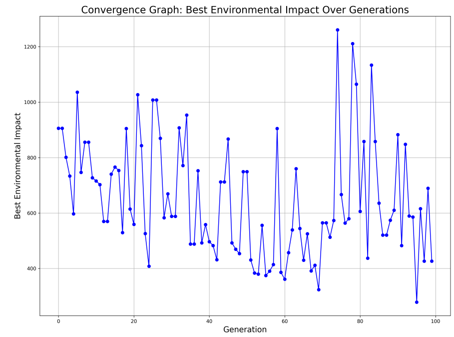
(a) Convergence of Best Revenue



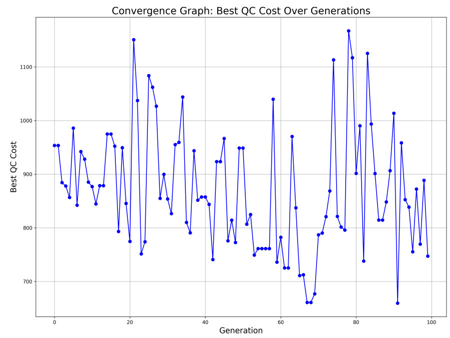
(d) Convergence of Best OTD



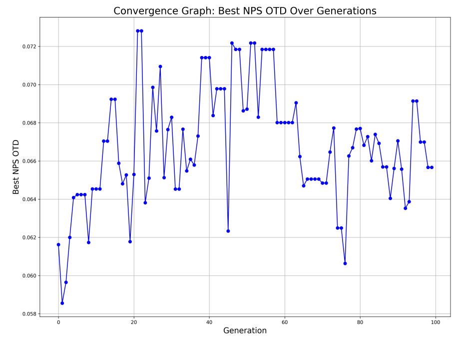
(b) Convergence of Best Total Cost



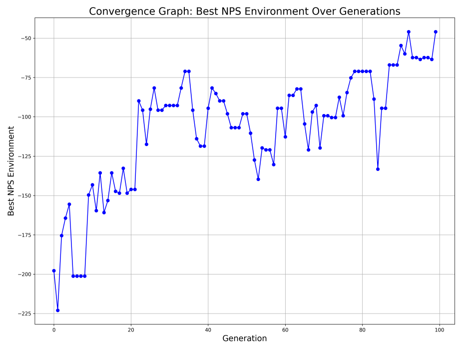
(e) Convergence of Best Environmental Impact



(c) Convergence of Best Quality Control Cost



(f) Convergence of Best NPS OTD



(g) Convergence of Best NPS Environmental Impact

Figure 19: Convergence graphs of objective functions against generation number. (Own Work)

7.7 Discussion: Analysis of NSGA-II Outputs for The Simulated Logistics Scenario

Through NSGA-II, Pareto solutions are found for the simulated SME automotive introduced in 17. Chapter 7.4 and 7.5 establish the optimisation objective functions and their corresponding parameter values. Table 14 shows solutions that are considered the Pareto best solutions, categorising each value based on the different objective functions. Table 15 establishes key ratios between the Pareto best solution objectives. Figures 18 illustrate the corresponding Pareto frontier for the different objective functions in two-dimensional figures. Figures 19 illustrate generations required for converging the best solutions.

To understand objective tradeoffs, it is crucial to plot each conflicting objective and analyse their behaviour. Figure 18a shows that higher revenues are associated with higher costs. However, specific data points indicate that achieving higher revenues with only moderate increases in costs is possible, suggesting Pareto optimal solutions. These exceptions likely represent scenarios where operational efficiencies are maximised, a key indication of effective SME management or innovative approaches within the algorithm. From Table 15, on average, the amount of Revenue brought by one unit of cost is 5.0.

The relationship between Environmental Impact and Revenue (£) in Figure 18b is less straightforward. While some high-revenue solutions coincide with high environmental impacts, others maintain moderate to low impacts, indicating effective management strategies or technological innovations that mitigate environmental damage. However, comparing the Pareto optimal solutions in Figure 15, producing one unit of environmental pollution will consume 19.1 units of cost and bring 105.90 units of Revenue.

In Figure 18c, Quality Control Cost (£) vs Revenue (£), a similar upward trend is noted as quality control costs rise with Revenue. However, the relationship is more pronounced than total costs, implying a more uniform management of quality control expenses across different revenue levels. Denoting that higher cost due to a higher amount of manufactured products results in higher possibilities of defects.

The trend of Figure 18d, On-time Delivery vs Revenue (£), is quite informative, suggesting an upward trend. OTD values are negative due to the negativity set by Eq 15, but this trend suggests that when deliveries align more closely with what customers ordered (i.e., high OTD, more positive), customers are likely to be more satisfied thus leading to higher revenues.

Similarly, Figure 18e, NPS Delivery vs OTD, follows an upward trend, with more convergence in higher OTD values, indicating that with higher OTD rates, customers are more inclined to give higher NPS delivery scores, thus being more satisfied. This confirms that timely delivery significantly enhances customer satisfaction.

Lastly, Figure 18f plots NPS Sustainability vs Environmental Impact, intuitively showing that lower environmental impacts lead to higher NPS Sustainability scores. However, solutions vary, with a slight clustering of regions with higher NPS for lower environmental impacts. This aligns with the requirements that lower environmental impacts lead to higher NPS environmental scores. Table 14 displays the possible best solutions for the supply chain configurations given in this chapter; NSGA-II flexibility allows SMEs to choose possible solutions, each with different tradeoffs.

Additionally, understanding convergence trends is essential in algorithm optimisation because it reveals how effectively an algorithm approaches the optimal solutions over successive iterations. Convergence analysis helps fine-tune algorithm parameters discussed in Chapter 6.1.2, ensuring a balance between exploring new solution spaces and exploiting known ones and assessing the algorithm's overall efficiency. It also provides insights into the problem's complexity and the tradeoffs between conflicting objectives. Recognising these trends is vital for deciding when to stop the algorithm and comparing the performance of different optimisation strategies.

The convergence of Revenue in Figure 19a shows variations but with a general tendency towards higher revenue solutions over generations. This indicates that the algorithm effectively maximises Revenue, a primary objective of SMEs (Qamar et al. 2020, Dinsdale & Bennett 2015). However, in Figure 19b, the total cost demonstrates variability without apparent convergence to a lower value, possibly indicating the inherent tradeoffs between different cost-related objectives. Figure 19c shows fluctuations in QC cost, a characteristic of a search space with multiple local optima. While it appears to converge to a lower bound, the slight variations suggest competing objectives that prevent a steady decrease in QC costs. The upward convergence of Figure 19d suggests that the algorithm is effective at maximising OTD, aligning with SME requirements. This effectiveness is reflected in Figure 19f, where NPS delivery is also optimised effectively over generations.

Similarly, it effectively minimises environmental impact in Figure 19e, a noticeable trend to converge to lower values, aligning with Industry 5.0 requirements. Lastly, this effectiveness is reflected in NPS environmental with a gradual increase in the values, moving towards less negative (better) scores over generations. This improvement suggests an effective optimisation towards better environmental practices as perceived by customers and stakeholders.

These graphs indicate that the NSGA-II algorithm is actively searching through the solution space, balancing tradeoffs between objectives. The lack of convergence in some objectives might suggest that the solution space is complex, with many Pareto-optimal solutions. These convergence patterns are common due to the complexity of balancing multiple objectives. It may also reflect the real-world complexity of business objectives where perfect optimisation of one aspect can lead to the decrease of another, hence the importance of a balanced approach towards multi-objective optimisation.

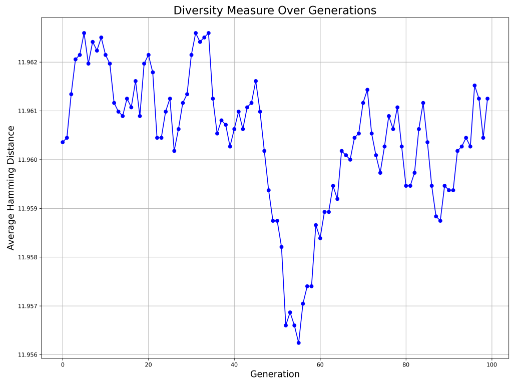


Figure 20: Hamming Distance (Own Work)

To analyse the crowding distance discussed in Chapter 5.1, Hamming distance is utilised, noted by Bookstein et al. (2002), which measures the difference between solutions by counting the points at which the corresponding solution elements differ. Observing fluctuations in the average Hamming distance, Figure 20 shows no clear trend toward increasing or decreasing diversity. This suggests that the algorithm is maintaining genetic diversity through the optimisation process. This is a positive sign as it indicates that the algorithm is not converging prematurely to a small area of the search space, which could lead to local optima. Maintaining diversity is essential for the effectiveness of an evolutionary algorithm like NSGA-II, ensuring a good exploration of the solutions and the potential to find an actual Pareto front. A diverse population allows the algorithm to explore various tradeoffs between objectives, which is particularly important in multi-objective optimisation problems where there are many possible solutions with different balances of objectives.

8 Management Strategy Development For SMEs

Building on the technology integration problems inherent to SMEs discussed in Chapter 2, customisation possibilities of NSGA-II in Chapter 6, and the integration framework established in Chapter 7, this chapter elaborates on strategies for adopting the NSGA-II algorithm across various dimensions of SME operations transitioning from Industry 4.0 to Industry 5.0. It underscores the synthesis of advanced algorithmic integration with strategic organisational and operational enhancements.

8.1 Technological Integration Strategy

Technological Integration Strategy

For SMEs, integrating the NSGA-II algorithm necessitates a meticulous assessment of existing infrastructure, as discussed in Chapter 2.5. According to Kamble et al. (2018) and Hansen et al. (2024), system compatibility evaluations should encompass computational capabilities, latency benchmarks, and data throughput requirements to ensure proper integration; this was discussed in the algorithm requirements in Table 11.

For example, a study on SME workforce scheduling optimisation in a warehouse implemented middleware that facilitated real-time data exchange between their ERP, DXClan system, and a newly adopted NSGA-II framework, resulting in improvement of work and data efficiency (Vu & Nguyen 2022).

Advanced Applications of Industry 4.0 and 5.0 Technologies

IoT devices can be strategically utilised to capture real-time logistics data, enhancing the NSGA-II algorithm's parameter input quality (Rezaei et al. 2017, Hachem et al. 2021). As per Vu & Nguyen (2022), integrating IoT with NSGA-II significantly reduces decision-making delays and improves accuracy in dynamic environments. SME can effectively utilise blockchain to increase efficiency (Singh 2024); this technology can also be leveraged to authenticate and log decisions made by NSGA-II. This ensures that supply chain transactions are immutable and traceable, enhancing business transparency and safety, as noted by (Nartey et al. 2022).

8.2 Organisational Strategy

Effective Change Management

A detailed SME change management framework involves both leadership and firm elements, as illustrated in the model by van Akkeren & Harker (2003), Figure 21, which suggests assessment of leadership and firm characteristics to facilitate technology acceptance, while also analysing ROI of that technology. Training programs should be designed based on role-specific requirements, ensuring that SME workforce and executives understand their roles in leveraging NSGA-II driven processes. For example, technicians receive hands-on training on system troubleshooting and maintenance, while decision-makers are educated on interpreting algorithmic outputs for strategic decisions (Stentoft et al. 2021, Masood & Sonntag 2020).

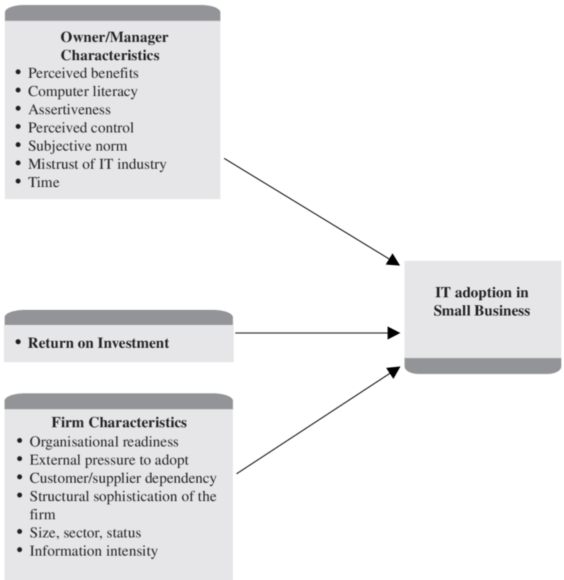


Figure 21: Framework of SME Adoption of Innovations (Taken from (van Akkeren & Harker 2003))

Developing Policies and Governance Frameworks

To align with human-centric values of Industry 5.0, establishing policies around the ethical use of NSGA-II and decision-support systems are crucial. Policies should address data privacy, algorithmic bias, and user accountability to align with Industry 5.0 requirements (Xu, Lu, Vogel-Heuser & Wang 2021). A review framework should include monthly review of algorithm performance against core KPIs, ensuring that it remains effective and aligned with SME strategic objectives (Saliji 2021, Aghazadeh 2003).

8.3 Operational Strategy

Process Re-engineering for Algorithmic Integration

Re-engineering frameworks to accommodate NSGA-II involves redesigning workflows to eliminate redundancies and enhance data flow efficiency. Simulation tools like Arena Simulation Software can model and visualise potential changes and their impacts on throughput and productivity. An example of operational strategy may include implementing dynamic pricing models, where NSGA-II adjusts product prices in real-time based on inventory levels and market demand (Deb et al. 2002, Bandyopadhyay & Bhattacharya 2014).

Performance Monitoring and Continuous Improvement

Metric monitoring strategies should employ advanced analytics to evaluate the NSGA-II algorithm's impact on supply chain metrics such as delivery times, order accuracy, and customer satisfaction. Benchmarking against industry standards can highlight performance gaps and improvement areas in operational efficiency (Zhang et al. 2003, Saliji 2021). A continuous improvement protocol might involve implementing a feedback loop into the NSGA-II where operational parameters is regularly refined (Hachem et al. 2021).

8.4 Scalability and Future-Proofing Strategy

Scalability Considerations

Discussing scalability involves increasing computational capability and resources and optimising the algorithmic efficiency to handle larger datasets (Hansen et al. 2024, Deb et al. 2002). Modular strategies, such as adopting scalable Industry 4.0 cloud services that allow for more extensive data storage without significant downtime or capital expenditure, are crucial (Dirican 2015, Papulová et al. 2022).

Preparing for Future Technological Advances

Proactively engaging with technological trends in new sensors and updates is crucial for maintaining algorithmic relevance. Future-proofing involves evaluating the potential integration of emerging technologies like advanced machine learning models and AI that could significantly enhance NSGA-II or its future models, computational capabilities, and efficiency.

9 Conclusion

This chapter summarises the findings of this dissertation underscoring the significant potential of adapting and scaling algorithmic models like the NSGA-II to enhance supply chain operations in SMEs transitioning towards Industry 5.0.

9.1 Overall Conclusion

This dissertation was centred upon the research question in Chapter 1.3. Through extensive analysis, this dissertation has addressed the core objectives outlined in Chapter 1.2 and shed light on the nuanced challenges and opportunities presented by the transition from Industry 4.0 to 5.0.

The dissertation begins with a comprehensive review of existing literature, Chapter 2, identifying knowledge gaps in applying advanced algorithmic models tailored to the operational realities of automotive SMEs. The literature highlighted the lack of practical strategic frameworks that effectively integrate human-centric approaches of Industry 5.0 with technological advancements of Industry 4.0, an area where this dissertation contributes new insights. The knowledge from the systematic review established a foundation for exploring practical algorithms suitable for SMEs.

In Chapter 3, the research methodology was adapted from Saunders et al. (2012) to support the exploration and adaptation of algorithmic methods using a mixed-methods approach. This methodological framework provides a robust analysis, combining quantitative data and qualitative insights, thus allowing a deeper understanding of the algorithm's impacts on SME supply chain optimisation. The iterative abductive research approach and the research philosophies allow the continuous adaptation of algorithmic models based on the literature, ensuring that the solutions are practical and effective.

The methodological analysis conducted in Chapters 4 to Chapter 6 provided in-depth analysis into specific algorithms, among others, NSGA-II, PSO, and MILP, through an extensive filtration and selection process based on SME constraints and algorithm capabilities, NSGA-II was the one chosen to be adapted. This adaptation was critically analysed in Chapter 7, where the modified NSGA-II algorithm was evaluated through simulation models developed using Python and DEAP library and SME objective functions that align with their priorities, as outlined in Chapter 3 and 2. The simulations highlight the enhanced applicability and ease of setup of NSGA-II in optimising SME supply chains in alignment with Industry 5.0 principles, demonstrating improvements in sustainability and operational efficiency.

The final analysis discussed in Chapter 8 refocused the research findings on the research question, showcasing how the adapted algorithm could be practically implemented within SMEs from operational to organisational settings. The results indicated that through strategic algorithmic adaptations, SMEs could significantly improve their supply chain forecasts and processes, enhancing their competitiveness and decision-making. These findings corroborate with the theoretical discussions in Chapter 2 and provide new insights into the practical applications of algorithmic models in businesses.

In conclusion, this dissertation highlights that the strategic adaptation of supply chain optimisation algorithms, customised to the unique constraints of SMEs, can significantly propel these enterprises towards successful integration of Industry 5.0 innovations. This dissertation has demonstrated how SMEs can utilise algorithmic solutions to enhance operational efficiency and prioritise broader value-driven metrics. Thus providing a significant contribution to insights on industrial transitions and SME operational efficiency.

9.2 Contributions to Academia and Industry

To Academia

Expansion of existing knowledge: Addresses a gap in existing literature by focusing on the application of algorithmic models specifically customised to the operational needs of automotive SMEs. As discussed in Chapter 2, previous literature largely concentrated on larger enterprises and algorithmic solutions in general and have not fully considered the integration of value-driven performance metrics other than sustainability. By exploring these gaps, this study enriches the academic content regarding supply chain optimisation in the context of Industry 5.0.

Theoretical to Practical Integration: This dissertation bridges theoretical concepts from industrial management and algorithmic concepts, creating a multidisciplinary understanding of how technological advancements can be practically applied to real-world problems. Chapter 4 to 6's detailed analysis of specific algorithms and their potential modifications introduces new theoretical insights that can guide future development.

To Industry

Enhancing SME Competitiveness: From Chapter 6 and 7, the adaptation of NSGA-II algorithm specifically for SMEs enhances their ability to integrate Industry 4.0 technologies and 5.0 human-centric values into their operations. This contribution is crucial as it provides SMEs practical tools to improve efficiency and sustainability, enhancing their market competitiveness.
Operational Improvement: The adapted algorithm facilitates better decision-making within SME supply chains by optimising various performance and value-driven metrics. Chapter 7's simulation results demonstrate how these improvements can be achieved, offering SMEs tangible strategies to enhance their operational effectiveness.
Strategic Planning: Chapter 8, highlights how business can align their operational strategies with broader business industry trends towards more integrated, human-centric processes. This insight would allow industry leaders to consider fostering an environment for SMEs to thrive amidst industry shifts.

9.3 Limitations and Future Research

While insightful, this dissertation presents certain limitations that allow for future research opportunities. These limitations come from the scope of the study and methodological constraints in which the research was conducted.

Scope of Study & Methodology Limitation

Focus on the automotive sector: This dissertation was done under the specific considerations of SMEs within the automotive industry. While this focus allowed for an in-depth analysis of unique challenges and opportunities within this sector, the findings are not fully generalisable to SMEs in other sectors. As industries may have different operational constraints and levels of technological integration, thus the adaptations of the NSGA-II algorithm and its applications might differ.
Geographical Limitations: The dissertation primarily considered SMEs based in regions with advanced technological capabilities. This geographical focus limits the applicability of the conclusion to regions where similar technological and industrial capabilities exist. SMEs in less developed countries may have a different set of challenges.
Data Collection: Reliance on secondary data and existing literature might limit the quality of

insights into recent advancements. Primary data collection, such as interviews and surveys directly from SMEs, could give SMEs more current challenges and opportunities.

Simulation-based Analysis : While simulations provided extensive insights into the potential efficiencies and improvements, they inherently lack the unpredictability of real-world application. Simulations are controlled by their parameters, and thus, they may not fully capture all real-world variables.

Future Research Directions

Wider Industry Application: Future research could explore how the adapted NSGA-II algorithm could be implemented in SMEs across different sectors. By identifying the sector-specific challenges and opportunities to enhance algorithm generalisability.

Expanded Geographical Focus: Further studies could include SMEs from various geographical regions, possibly focusing on third-world countries. This would test the robustness and adaptability of the current findings and enhance understanding of global SMEs.

Infant Algorithm Adoptions: Future research could explore the current adaptation framework for SMEs but through the lens of NSGA-III, a recent version of NSGA-II that was recently introduced.

Real-time Data Collection Framework: Establishing a real-time data collection framework within SMEs could allow for continuous improvement and adaptation of the algorithms based on live operational data, greatly enhancing precision.

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