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Article

Supply Chain Optimization via Simulation and Path Planning Algorithms: An Overview

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Abstract: The supply chain is a process that manages the flow of goods, information, and funds from production to consumption. It aims to reduce costs, improve efficiency, and meet customer needs. Technologies and sustainability are key factors in modern supply chain management. The primary objective of this paper is to provide a comprehensive review of current literature that use optimization-based simulation techniques to address the specific challenges inherent in these supply chains. However, the second objective is to present an overview of path planning algorithms. This paper offers insights into recent advancements and emerging trends in the field by examining modeling methods, decision support systems, and innovative approaches. Tailored for researchers and practitioners, this synthesis aims to enhance understanding of current developments and guide future research in optimizing supply chains through simulation. In this paper, we present the utility of using planning algorithms in the supply chain to increase the performance in terms of exportation transports.

Keywords: supply chain management; optimization based simulation; path planning algorithms

1. Introduction

The supply chain [1–6] is a vital component of the global economy, facilitating the efficient movement of goods, materials, and information from point of origin to point of consumption [7,8]. It incorporates a broad range of activities including sourcing raw materials, manufacturing, storing, distributing, and delivering finished products to customers.

Effective supply chain management is essential for ensuring customer satisfaction, reducing costs, and enhancing competitiveness. Technological advancements such as information systems, tracking technologies, and data analytic have transformed the way supply chains are managed, enabling greater visibility and control over operations.

Optimizing supply chain management is a strategic approach aimed at improving the efficiency and profitability of the entire process, from production to distribution, including the storage and transportation of goods. This approach can focus on various key aspects to achieve this goal. Firstly, it encompasses inventory management, which aims to balance stock levels to minimize storage costs while ensuring adequate product availability [9]. Secondly, production planning plays a crucial role in avoiding downtime and optimizing the use of available resources [10]. Optimizing routes and modes of transportation is also essential to reduce costs and delivery times, taking into account logistical constraints such as vehicle capacity and delivery schedules. Effective warehouse organization helps minimize storage costs and goods processing times by optimizing storage space and good flows [11]. Close collaboration with partners throughout the supply chain is another key aspect, improving coordination and reducing delays, errors, and costs associated with good flows. Finally, the use of advanced technologies (inventory management systems, resource planning systems, supply chain management software, tracking and tracing solutions, the Internet of Things, and artificial intelligence) helps automate processes and make more informed decisions. In the dynamic landscape of the industry, the integration of simulation technologies into the supply chain has emerged as a key driver for optimizing its efficiency and resilience. The complex nature of the supply chain, characterized by seasonality, demand fluctuations, and susceptibility to external factors, underscores the importance of proactive and adaptive strategies. Simulation is a valuable tool for enhancing supply chain management efficiency by enabling companies to model different scenarios and processes. It allows testing of various strategies, identifying potential bottlenecks, and making informed decisions to improve performance. Simulation has been widely integrated into the literature to optimize supply chain management in its various operational facets. Indeed, simulation is a powerful tool for identifying areas for improvement and enhancing overall efficiency throughout the logistics process. By systematically testing and refining different parameters, such as production schedules, stock levels, and distribution strategies, stakeholders can determine optimal configurations that minimize costs and maximize throughput. It also enables forecasting. It assists in evaluating the effects of supply chain modifications, such as introducing new products, adjusting production capacity, or dealing with disruptions in the network. The facet of delivery optimization via simulation has remained under-explored.

The aim of this study is to build a simulation-based optimization methodology that integrates the delivery management aspect. Our goal is to optimize transportation by integrating path planning algorithms [12–16] to find the shortest path between the production center and the consumer in the simulation model of a supply chain. This article is organized as follows: Section 1 focuses on the state of the art of optimization-based simulation in supply chain management. Next, we will provide a detailed description of planning algorithms in Section 2. Section 3 will propose a methodology for integrating path planning algorithms into the simulation. We will conclude with a conclusion and future outlook.

2. Literature Overview

In this section, we will focus on two essential aspects: simulation-based optimization and planning algorithms. Firstly, we will review the literature on simulation-based optimization in supply chain management. This will include discussing the various approaches and methodologies used in simulation-based optimization, as well as the benefits and challenges associated with this approach. We will also examine case studies and examples of how simulation-based optimization has been applied in real-world supply chain scenarios, highlighting the impact it has had on improving efficiency and performance. In the second part, which focuses on planning algorithms, particularly in the context of path planning [17–20], we aim to present a comprehensive review of the latest advancements. This review will encompass a discussion on various path-planning algorithms frequently employed.

2.1. Optimisation Based Simulation Supply Chain Management

Simulation-based optimization is a powerful method in supply chain management for enhancing operational efficiency and decision making. Businesses can gain insights into supply chain dynamics and identify strategies for performance improvement by integrating simulation modeling with optimization techniques. Several studies have successfully applied simulation-based optimization in areas such as inventory management, production planning, and distribution network design. For instance, vostriakova et al. [21] seeks to improve the overall efficiency of the logistical distribution system for fruit products by maintaining product freshness, minimizing stock levels, and reducing waste. They use a Monte Carlo simulation model to evaluate the economic performance of the agricultural system. Additionally, they conduct a comparison of the efficiency of the agri-food supply chain and apply Lean thinking methodology to optimize the logistics chain. This method aims to maximize value for the customer while minimizing waste. Next, Xu et al. [22] delves into the development of Internet of Things (IoT) technologies and agricultural land sensors for real-time monitoring and control of crops, with a focus on bolstering food security. Employing a Vensim simulation model and least squares algorithms, they aim to refine the accuracy of sensor measurements (including soil moisture and CO_2 sensors) for cereals, ensuring the reliability and stability of data. Furthermore, they leverage an artificial neural network algorithm to enhance the security and efficiency of the network. Also, Tundys et al. [23] provides clarity on the concepts surrounding the short chain and identifies activities within these structures that can have economic implications. They use the Arena simulator to model the manufacturing system. Furthermore, they incorporate Multi-objective optimization through OptQuest to ascertain performance measurement estimates and to identify optimal delivery proportions for various market types (face-to-face, proximity, and extended spatial).

Othman et al. [24] provides an overview of simulation and optimization in supply chain management. It emphasizes the use of Arena or Matlab for discrete event simulation and focuses on the Meta-heuristic approach (genetic algorithms [25], PSO, etc.) to minimize total inventory costs and maximize service levels.

Daniel et al. [26] suggest the use of a genetic algorithm to optimize inventory levels, employing the Random Search Procedure (RSP) to assess the effectiveness of the genetic algorithm. But, Liu et al. [27] leverage the Information Service Business based on big Data and Block-chain (ISBD) to cut costs, minimize the risk of unsold inventory, and bolster security credibility. Big Data is instrumental in obtaining precise information, while Block-chain guarantees data authenticity and sharing. The concurrent application of Big Data and Block-chain yields a resilient data-focused chain. So, Raba et al. [28] explore hybrid simulation and optimization methods to cut down on food inventory and reduce the occurrence of erroneous orders. The optimization method is applied to identify optimal configurations, while the simulation approach is used to model and assess performance. In this instance, they employed the simheuristic algorithm to tackle the multi-period stock routing problem, which comprises an optimization component for exploring promising solutions and a simulation component for evaluating solutions in a stochastic environment. Furthermore, they integrated Monte Carlo simulation into their approach.
Hassine et al. [29] outlines a simulation of the product manufacturing process, aiming to integrate ecological and economic objectives. The methodologies employed in this research are rooted in decision support principles and multi-objective optimization. Decision support is facilitated through the Evamix and Promethee methods, while swarm algorithms are used for optimization purposes. Also, Amer et al. [30]dedicate to developing a simulation model for an actual orange supply chain using ExtendSim. The main focus is to examine the effects of modifying order quantities in response to demand fluctuations. The overarching goal is to minimize food waste, deliver higher-quality fresh products, and reduce emissions, addressing environmental concerns. Simultaneously, the study aims to uphold maximum profitability and an acceptable level of service, considering social aspects. Furthermore, they use performance measures, including economic factors such as total chain cost and profits, to evaluate the system.

Vieira et al. [31] addresses the intricate task of designing a Sustainable Supply Chain Network (SCND) while incorporating risk management. It introduces a Simulation-Based Decision Support System (SBDSS) applied to a real case study involving the SCND of Portuguese wine. Often overlooked in existing literature, the study employs a simulation approach with agent-based modeling and a simheuristic to generate non-dominated solutions by focusing on the wine industry. Results reveal Pareto-front solutions that incorporate sustainability and risk considerations, emphasizing the significant impact of transportation risks on performance compared to risks associated with energy and raw material prices. This research makes a substantial contribution to understanding the challenges of SCND design in the context of sustainability and risk management.

Gallego et al. [32] develop an innovative approach and a specific tool to enhance the capabilities of smallholders in addressing disruptions effectively. The proposed model analyzes the effects of risks and assesses preventive policies, mitigation strategies, and responses to both internal and external risks. This comprehensive analysis is conducted at three crucial levels: farmer's organization, the supply chain, and the overall environment, with a particular focus on Corporate Social Sustainability. The central objective is to strengthen the resilience of smallholders by optimizing the agro-food supply chain and the associated environment within farmer organizations, taking into account all relevant stakeholders. The ultimate outcome of the model is to provide practical recommendations to fortify the long-term viability and capabilities of smallholders in the face of potential disruptions. In addition, li et al. [33] explores the impact of interconnected supply chains on economic development, emphasizing productivity, distribution, and revenue for improved standardization. It addresses the need to optimize the industrial economy by reducing overhead costs, particularly in unplanned supply chain distributions. Using Particle Swarm Optimization (PSO), the study introduces a Connecting Model (CM) to identify cost-effective circular chain designs for product distribution. The focus is on minimizing overhead costs, and the iterative process identifies optimal solutions for standardized supply chain management. But, Nafi et al. [34] delves into the intricacies of supply chain problems, specifically focusing on-stock chains. The complexity arises from the variety and antagonism of performance indicators, coupled with the challenge of understanding the effects and interactions of different performance drivers in relation to these indicators. The primary objective is to explore the contribution of Machine Learning to establish mathematical links between evaluation parameters of an on-stock supply chain and its operational parameters. The study is grounded in an academic case that seeks to mathematically formalize the issue of delivery delays in an on-stock supply chain. Multiple Machine Learning algorithms were tested and compared. However, the impossibility of obtaining a labeled data set from the real system underscores the necessity of using a simulation system. Particularly, discrete event simulation is used to generate the required data set for subsequent analysis. Schwartz et al. [35] propose a simulation-driven optimization framework that leverages simultaneous perturbation stochastic approximation (SPSA). This framework is designed to optimize parameters for decision making policies based on internal model control (IMC) and model predictive control (MPC). These policies are tailored for inventory management in supply chains operating under uncertain supply and demand conditions. The utilization of the SPSA technique enhances the performance and functionality of these decisions algorithms. This is exemplified through case studies focusing on the concurrent optimization of controller tuning parameters and safety stock levels in semiconductor manufacturing-inspired supply chain networks. The results demonstrate substantial reductions in safety stock levels and financial benefits while maintaining satisfactory operational performance in the supply chain. Wu et al. [36] focuses on improving inventory optimization in the Fresh Agricultural Products (FAPs) supply chain using neural networks. It introduces a soft computing method to address uncertainty in the system, constructing a connection entropy within the inventory system. The paper proposes an integrated inventory optimization model for FAP supply chains based on the BP neural network, overcoming challenges with a Particle Swarm Optimization (PSO) algorithm. Results show that the PSO-BP neural network converges significantly faster than the BP neural network. Simulation experiments using vnsimPLE confirm the substantial optimization impact of FAP supply chain integrated inventory based on the BP neural network. Rabet et al. [37] aims to integrate production, maintenance, and delivery operations within the supply chain, addressing common gaps in supply chain management. Through a case study with a fertilizer producer facing seasonal demand, it presents a mathematical framework and two multi-objective simheuristics designed to tackle the Integrated Production, Maintenance, and Distribution Scheduling Problem (IPMDSP). These strategies aim to minimize maintenance duration, distribution costs, and customer dissatisfaction arising from delayed deliveries. The findings underscore the effectiveness of the simheuristic approach using NSGA-II compared to MOPSO. Additionally, the comparison between deterministic and stochastic approaches underscores the importance of considering uncertainty caused by maintenance activities. The proposed simheuristics significantly improved objective minimization in the fertilizer producer case study.

Maheshwari et al. [38] examine how the digital twin method can be used to improve procurement, production, and distribution strategies (PPDs) within a medium-sized food processing company. This involves the integration of mixed-integer linear programming (MILP) with agent-based simulation (ABS), the model considers industrial symbiosis opportunities, focusing on interval and sequence variables in a constrained environment. The research aims to enhance digitization levels while optimizing make-span and lead time. Findings indicate that the digital twin approach significantly improves supply chain productivity, impacting various aspects such as make-span time, data redundancy, scheduling, and overall equipment effectiveness. The seamless integration of PPDs boosts production flexibility, achieving a notable 94% service level. Real-time simulation assists managers inaccurately estimating replenishment points, optimizing operations. The study highlights tangible benefits, including a 65% utilization of pasteurizer and aging vessels, 97% utilization of the freezer, and a 6% reduction in backlog, showcasing improved efficiency through digital twin-guided PPD implementation. These studies highlight the effectiveness of simulation-based optimization in addressing complex supply chain challenges and achieving measurable performance enhancements. Aroba et al. [39] tackle significant operational and productivity challenges in hospital management through the administration of 50 questionnaires and the utilization of Cronbach's Alpha to analyze responses. They provide an in-depth examination of the SAP ERP system's digital transformation operations in hospitals and healthcare centers, specifically in supply chain management.

Table 1 presents recent's papers, considering the optimization method and simulation tool based on several performance criteria, including Economic, Security, cost, robust, stock, routing,… In this table, we notice that there are different works in various application areas of the supply chain with the use of different simulation tools and optimization methods. However, it is evident that there are not many studies that consider optimization at the transport, specifically using path planning algorithms to optimize transport, especially for exports.

Table 1. Overview of simulation based optimisation in supply chain.

	Optimization Method	Simulation Tool	Performance	Field of Application	Real Uses Case
vostriakova et al. [21]	Lean thinking	Mont carlo	Economic	Agricultural System	Yes
xu et al. [22]	IOT/ANN	Vensim	- Realiability - Stability - Security	Digital Technology Empowers Grain	Yes
tundys et al. [23]	OptQuest	Arena	Optimal delivery	Organic Product	Yes
othman et al. [24]	Meta-heuristic	Arena	Total inventory cost	Supply chain managment	No
Daniel et al. [26]	Genetic algorithm	-	Robustess Base stock	Serial supply	No
liu et al. [27]	Big data+ Blockchain	Numerical simulation	-Minimize risk security - Reduce cost	Green agrifood supply chain	Yes
raba et al. [28]	IOT	Mont carlo	Accurate estimation of the expected cost - Inventory and routing costs	Animal feed supply chain	Yes
hassine et al. [29]	particle swarm	——	- Economic - Ecological	Sustainable manifacturing	Yes
amer et al. [30]	———	ExtendSim	- Minimize food wastage - Higher quality fresh produce - Lower emission	Actual oranges supply chain	Yes
Vieira et al. [31]	OptQuest	Arena	- Risk of energy and raw material - Transportation risk	Wine supply chain	Yes
Gallego et al. [32]	Digital Twin	Vensim	-Reduce the effect of risk - Optimise resource consumption	Agri-food supply chain	Yes
Li et al. [33]	Particle swarm	————	- high-precision supply chain connectivity - Low cost overheads	INDUSTRIAL SUPPLY CHAIN MODEL	Yes
Nafi et al. [34]	Machine learning	Arena	Optimal safety stock order quantity	On stock chain	Yes
Schwartz et al. [35]	PSO	Simulation based optimisation	-reduce controller tuning and safety stock	Process control policies for inventory management	Yes
Wu et al. [36]	Back propagation neural network	VensimPLE	Effectiveness of comprehensive inventory	Fresh agricultural Product supply chain	No
Rabet et al. [37]	PSO+Non dominated sorting genetic algorithm	———	-Minimizing maintnance duration - Distribution costs	Fertilizer product	Yes
Maheshwari et al. [38]	Digital twin+ linear programming	AnyLogic	- improve makespan time - Date redondancy - Capacity utilisation	Food supply chain	Yes

3. Path Planning Algorithms

Path planning is a fundamental problem in robotics, autonomous vehicles, and logistics. The goal is to find an optimal path from a starting point to a target location while avoiding obstacles and adhering to constraints. Various algorithms have been developed to solve this problem, ranging from classical approaches like Dijkstra's algorithm to more advanced methods such as A* search, RRT, and D* algorithms. These algorithms differ in their computational complexity, optimally guarantees, and ability to handle dynamic environments. Understanding and comparing these algorithms are crucial for designing efficient and reliable systems in real-world applications.

Ben jmaa et al. [40] present an overview of the current state-of-the-art in path planning across different fields such as UAV, Robotic and video game. Additionally, we place particular emphasis on widely-used algorithms capable of meeting real-time constraints and accommodating dynamic re-planning. They present 45 articles on path planning approaches published between 2000 and 2023. These approaches are categorized into five classes: classical methods, heuristics, meta-heuristics, machine learning, and hybrid algorithms. Our analysis covers various objectives and constraints, including path length, time efficiency, collision avoidance, environment representation (2D/3D), and cost efficiency. We discuss these aspects and highlight the most commonly employed approaches within each class. But, this paper does not address works that use the supply chain as an application domain for path planning algorithms. In this paper, they give a comparative analysis between different algorithms and different criteria.

Qin et al. [41] provides an overview of path planning and obstacle avoidance methods for mobile robots, serving as a reference for researchers. It summarizes recent advancements in the field and discusses future research directions. The focus is on categorizing path planning algorithms into different types and reviewing their basic principles and key studies. The paper also discusses path planning for multi-robot systems and various types of robots, offering a comparison of these algorithms and proposing future research directions.

Li et al. [42] focuses on optimizing robot paths in logistics to enhance pickup efficiency, reduce resource waste, and minimize carbon emissions. Aligned with sustainable development principles, the research aims to promote environmental social governance by streamlining robot paths. To improve path planning and obstacle avoidance, the study proposes a fusion algorithm that combines an enhanced genetic algorithm with the dynamic window approach. The goal is to boost warehouse operation efficiency, cut logistics costs, and support the establishment of a green supply chain. The paper implements and evaluates this fusion algorithm for mobile robot path planning, demonstrating its effectiveness through comparative experiments. The research highlights the importance of advanced algorithms in optimizing robot paths and suggests avenues for future investigation.

Liu et al. [43] provides a detailed review of mobile robot path planning techniques, categorizing them into global and local methods based on the availability of environmental information. It discusses various environment-modeling methods and path evaluation techniques used in global path planning, including grid, topology, geometric feature, and mixed representation methods. Additionally, it explores the sensors commonly used in local path planning, such as laser radar and visual sensors. They categorizes mobile robot path planning algorithms into classical, bionic, and artificial intelligence algorithms based on their characteristics. Classical algorithms discussed include cell decomposition, sampling-based methods, graph search, artificial potential fields, and dynamic window approaches. Bionic algorithms, such as genetic algorithms, ant colony optimization, and Grey wolf optimization, are detailed, along with artificial intelligence algorithms like neural networks and fuzzy logic. They present a comparative analysis of key technologies in mobile robot path planning, using graphs and charts. These insights aim to guide future research in the field, providing a comprehensive overview of current techniques and methodologies.

In the realm of UAV path planning, Poudel et al. [44] explores various bio-inspired algorithms employed over the last decade. Notably, there is a lack of existing literature surveys on bio-inspired algorithms for UAV path planning. The study delves into these algorithms, examining their key features, operational principles, strengths, and limitations. A comparative analysis of these path planning algorithms is conducted, focusing on their distinctive features, attributes, and performance metrics. Additionally, the paper outlines the current challenges and future research directions in UAV path planning.

Wang et al. [45] examines transportation problems from both the supply and demand perspectives, focusing on path planning over time for stable supply and demand. Accurate road node information, supported by smart and connected network technologies, is crucial for this research. The study proposes a multi-vendor collaborative transportation strategy and tests it through simulation. Critical path nodes are identified and different transportation solutions are developed for them. The strategy proves effective in reducing transportation costs for suppliers. However, the study has limitations, such as not considering road access times, maintenance, avoidance, and weather. Future research could address these factors to offer more customized transportation services.

Xu et al. [46] presents a novel vehicle scheduling model designed specifically for the multi-objective distribution of agricultural products. The model aims to optimize various aspects of the distribution process, such as minimizing transportation costs, maximizing vehicle utilization, and ensuring timely delivery of products. To achieve these objectives, the model incorporates advanced algorithms and optimization techniques tailored to the unique challenges of agricultural product distribution.

4. Proposed Approach

In this section, we will provide an overview of how path planning algorithms can be used in supply chain logistics for optimization purposes.

Figure 1 show the proposed a general supply chain management. This figure illustrates a general supply chain from production to consumption. It shows that there are five essential steps in the supply chain: raw materials, manufacturer, wholesaler, retailer, and consumer, with product transportation required between each step.

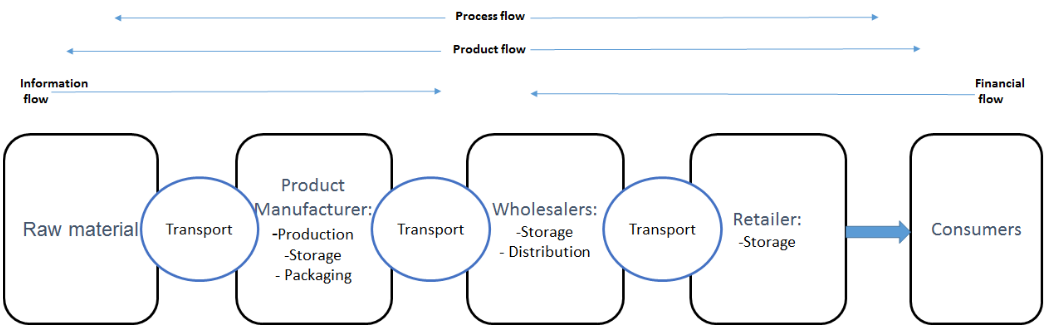

Figure 1. Steps of supply chain management.

- **Raw Materials**: Raw materials are the foundation of any manufacturing process, sourced from natural resources or suppliers. These materials can vary widely depending on the industry, ranging from metals and minerals to agricultural products or chemicals. Sourcing raw materials involves careful consideration of factors such as quality, cost, and availability. Suppliers play a crucial role in ensuring a reliable supply chain for raw materials, as disruptions in supply can influence production schedules and product quality.

- **Manufacturer**: The manufacturing stage involves transforming raw materials into finished products through various processes such as machining, assembly, or chemical processing. Manufacturers are responsible for ensuring that products meet quality standards and specifications. This stage requires efficient production planning, resource management, and quality control to optimize output and minimize waste. Manufacturers often invest in technology and automation to improve efficiency and reduce production costs.

- **Wholesaler**: serve as intermediaries between manufacturers and retailers, buying products in bulk and selling them to retailers at a markup. They play a critical role in the supply chain by providing storage, distribution, and logistics services. Wholesalers help manufacturers reach a broader market by distributing products to retailers across different regions. They also offer economies of scale to retailers by allowing them to purchase goods in large quantities at discounted prices.

- **Retailer**: Retailers are the final link in the supply chain, selling products directly to consumers through various channels such as brick-and-mortar stores, online platforms, or catalogs. Retailers play a key role in marketing, merchandising, and customer service, influencing consumer-purchasing decisions. They must manage inventory effectively to meet customer demand while minimizing holding costs. Retailers also focus on providing a positive shopping experience to build customer loyalty and drive repeat business.

- **Consumer**: Consumers are the ultimate end-users of products, purchasing goods for personal use or consumption. Consumer behavior and preferences drive demand in the market, influencing the production and distribution of goods. Meeting consumer need requires businesses to understand market trends, offer innovative products, and provide exceptional customer service. Consumer satisfaction is essential for building brand loyalty and maintaining a competitive edge in the market.

- **Transportation**: Transportation is a crucial step between each stage of the supply chain. It involves the physical movement of goods from one location to another, ensuring that products reach their intended destination.

4.1. Supply Chain Transporation Pooling Strategies

Jerbi et al. [47] describes a transportation pooling in various ways, but fundamentally, it involves a collaborative arrangement among multiple entities. This arrangement entails the voluntary consolidation of physical assets, information, and expertise to achieve collective economic, ecological, and financial benefits that would be challenging to attain individually. The structure of this collaboration can vary based on the parties involved, their resources, and the nature of the goods or services.

- Multipick (Pick-up Round): entails combining shipments bound for the same destination (customer) from various origins (suppliers). Consequently, items designated for the same customer from multiple suppliers are consolidated through a pickup process involving one or more vehicles.

Figure 2 show that the logistics network structure with multipick typically involves a hub-and-spoke model, where a central hub serves as a consolidation point for goods from multiple sources (warehouses, factories) and distributes them to their respective destinations (customers, warehouses). The hub is responsible for planning the pickup tours (multipick), scheduling the pickups and deliveries, and optimizing the routes to minimize costs and delivery times. This model allows for efficient use of transportation resources and better coordination of logistics operations.

- **Multidrop (Distribution Tour)**: Delivery starts from the same shipping location, delivering multiple streams of goods in the same vehicle to several geographically close delivery points or located on the same transport line. These delivery points can be single-client or multi-client. To be effective, multidrop requires circuit planning, scheduling of stops, and unloading times.

Figure 3 show that the logistics network structure with multidrop typically involves a hub-and-spoke model, similar to multipick. However, in the case of multidrop, the focus is on delivering goods to multiple geographically close delivery points or along the same transport line. This requires careful planning of routes, scheduling of stops, and coordination of deliveries to ensure efficient use of transportation resources and timely delivery to each drop-off point.

- **Supply Networks with Pickup Centers (Direct Final Delivery)**: Deliveries are made in two steps: upstream transport from industry to pickup centers and downstream transport from pick up centers to customers. The existence of intermediate centers increases the size of shipments and flows in the network, which has a positive impact on transportation (transportation cost, truck filling, etc.).

In Figure 4, the logistics network structure with a pickup center typically involves a hub-and-spoke model. In this model, the pickup center serves as a central point for receiving goods from multiple sources, such as warehouses or factories. The goods are then consolidated at the pickup center before being distributed to their final destinations. This structure allows for more efficient use of transportation resources and can help reduce transportation costs.

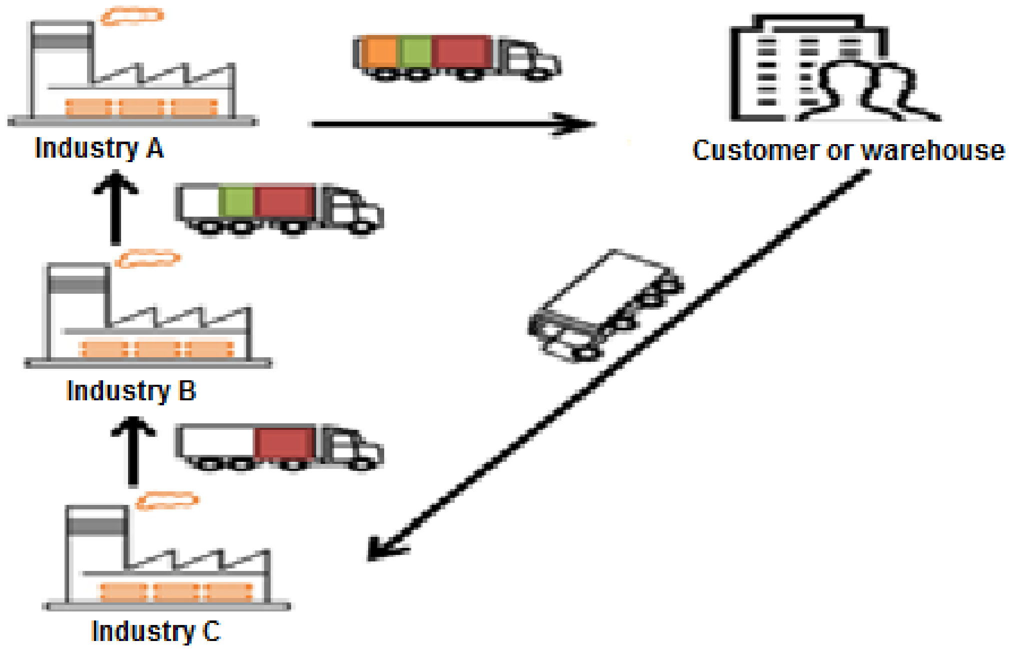

Figure 2. Logistics Network Structure with Multipick [47].

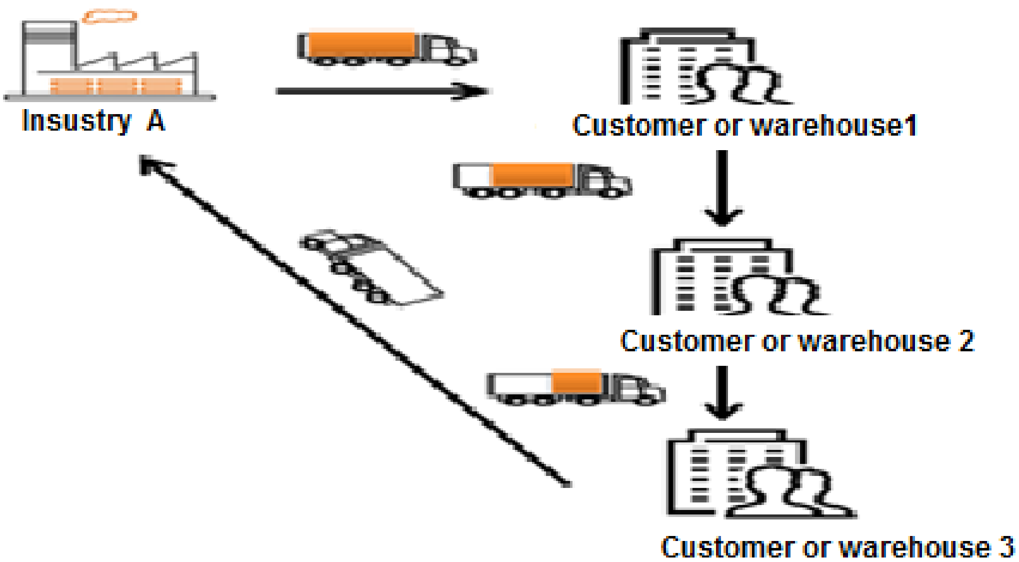

Figure 3. Logistics Network Structure with Multidrop Delivery [47].

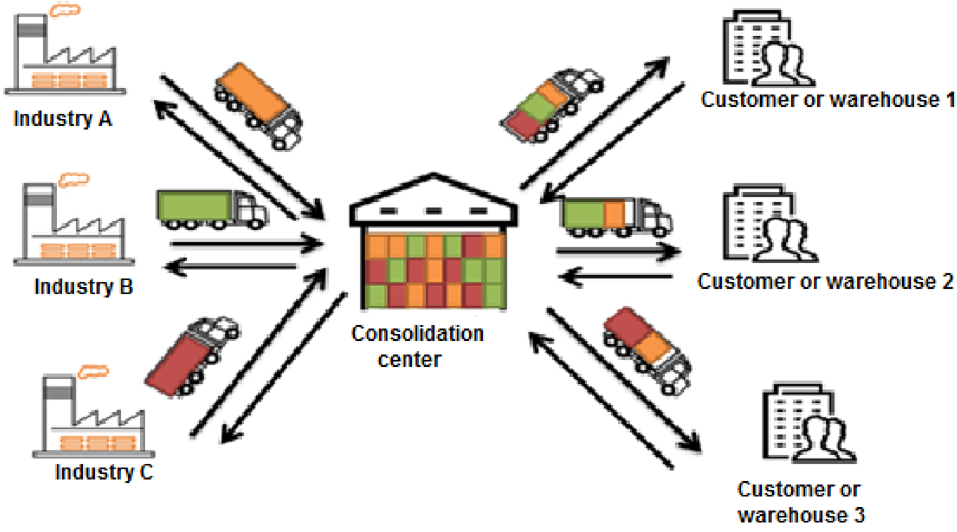

Figure 4. Logistics Network Structure with Pickup Center [47].

- **Supply networks with collection centers and final delivery through multidrop**: Deliveries are carried out in two stages. Upstream delivery is made directly to collection centers. However, final delivery is done by grouping the goods into multidrop, meaning delivery in the form of a vehicle tour to improve the filling rate.

Figure 5 shows a logistic network with a central pickup center and downstream delivery using multidrop. This process involves collecting goods at a central hub and then delivering them to multiple destinations on a single route, which improves efficiency and reduces costs.

- **Supply networks with collection centers and upstream delivery through multipick**: Upstream delivery is done by grouping goods in to multipick, meaning a delivery in the form of a vehicle tour between production industries to improve filling rates. However, the final delivery is made directly to customers.

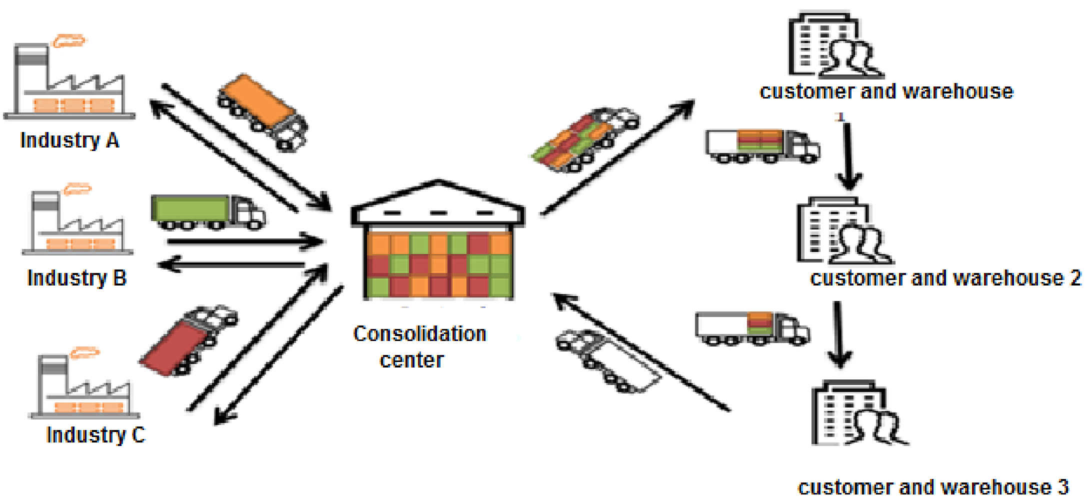

Figure 5. Logistic network structure with a pickup center and downstream delivery through multidrop [47].

Figure 6 present a structure involves a central consolidation center where goods from multiple sources are grouped together for efficient upstream delivery using multipick. It optimizes delivery routes and enhances the efficiency of the supply chain by reducing the number of trips needed for transportation.

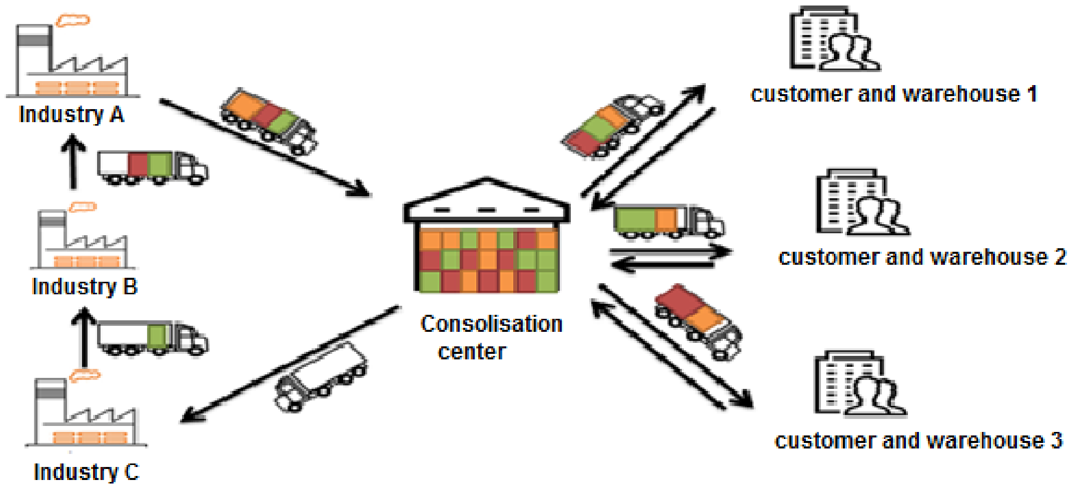

Figure 6. Structure of a shared logistics network with a consolidation center (upstream delivery in multipick) [47].

- **Supply Networks with Pickup Centers: Upstream Multipick and Downstream Multidrop Deliveries**: Upstream delivery involves grouping goods in to multipick tours between production industries, while downstream delivery entails grouping goods into multidrop tours between customers to improve fill rates.

Figure 7 illustrates a supply chain network featuring consolidation centers. Upstream delivery, indicated by multipick, involves the grouping of goods from production facilities. Downstream delivery, indicated by multidrop, shows the grouping of goods for customer delivery, highlighting the efficiency in vehicle loading and delivery optimization achieved through this network configuration.

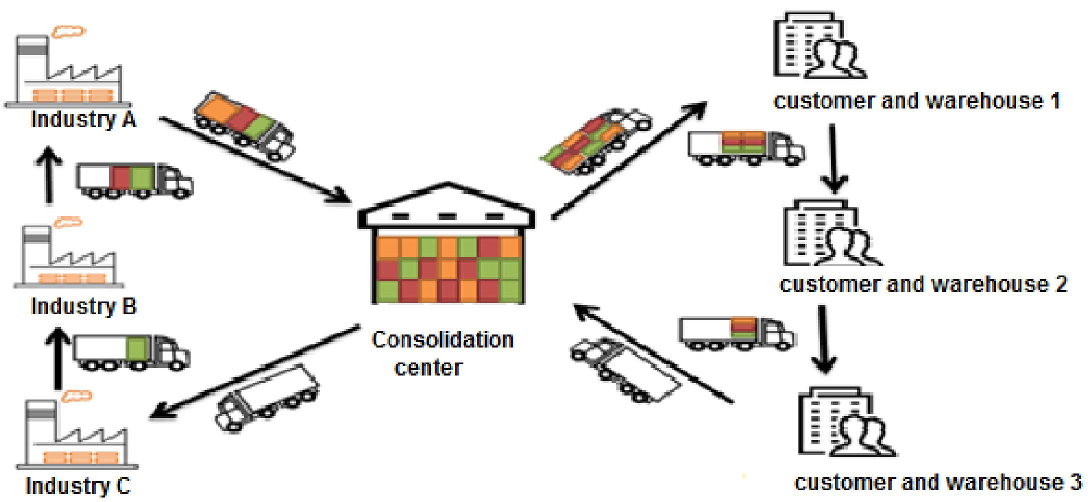

Figure 7. Supply Chain Networks with Consolidation Centers (Upstream Delivery by Multipick and Downstream Delivery by Multidrop) [47].

4.2. Proposed Optimization Method

In this part, we will explain our optimization methodology that we will use in my work.

In many scenarios, simulation-based optimization is conventionally performed in a static manner, where optimization algorithms are applied to the output of simulations after their execution. However, our methodology takes a dynamic optimization approach, integrating for example path planning algorithms directly into the simulation process. This integration allows for the real-time adjustment of parameters during simulation execution. This enables continuous and adaptive optimization throughout the simulation, providing better responsiveness to changes and unforeseen events while proactively enhancing system performance.

Our work is divided into several stages:

In the primary phase of our methodology, we focus on integrating shortest path algorithms into a specific simulation model. Our assumption in this step is that the trucks are chosen correctly from the outset. This model represents a logistical process that involves a multipick system downstream from the center and a multidrop system upstream from the center. The purpose of this integration is to optimize the routing of orders within this logistical process. We aim to determine the most efficient routes for orders to travel from their starting points to their destinations by applying shortest path algorithms. It's important to note that, at this phase, our focus is solely on optimizing routing decisions based on the locations of the orders' starting and ending points. Other decision making factors, such as vehicle capacity, time windows, and traffic conditions, are not yet taken into account. Also, this approach allows us to establish a foundation optimization framework within the simulation model, which can later be expanded to incorporate additional decision making factors for more comprehensive logistical optimization. In the second phase, we will delve deeper into the optimization of the shortest path selection process by considering additional decision making constraints. These constraints will be crucial in refining the routing decisions and improving the overall efficiency of the logistical process. Firstly, we will take into account the availability of trucks. This constraint involves ensuring that there are enough trucks available to fulfill the orders and that they are efficiently used throughout the process. Secondly, we will consider the physical characteristics of the trucks, such as their payload capacities. We can optimize the assignment of orders to trucks, ensuring that each truck is loaded to its maximum capacity while adhering to safety regulations by factoring in these characteristics. Lastly, we will explore the selection of trucks based on the size of the orders to be transported. This involves matching the size of the orders with the appropriate size of trucks, optimizing the transportation process and minimizing costs. We aim to enhance the efficiency and effectiveness of the logistical process, ultimately leading to cost savings and improved customer satisfaction by incorporating these additional decision making factors. In this step, we will explore the following three major criteria for indicators:

- **Economic Indicators**: These are defined in two subcategories: indicators of economic sustainability (vehicle load factor in weight and volume, warehouse filling rate) and overall financial indicators (balance sheet and evaluation of the business plan).

  - Economic Sustainability Indicators: These indicators assess the economic efficiency of the logistics chain. The vehicle loads factor in weight and volume measures the optimal use of transport capacities, which can indicate inefficiencies or improvement opportunities. The warehouse is filling rate evaluates the efficient use of storage space, which can influence storage and handling costs.

  - Overall Financial Indicators: These indicators provide an overview of the financial health of the company. The balance sheet examines the assets, liabilities, and equity of the company, providing a picture of its solvency and financial stability. The evaluation of the business plan analyzes the financial projections and objectives of the company, allowing an assessment of its profitability and long-term viability.

  We will be able to assess the economic performance of the logistics chain, identify areas for improvement, and make strategic decisions to optimize overall efficiency and profitability of the system by examining these indicators.

- **Quality Indicators**: These are the service rates within a logistics chain. Three categories of service rates are considered: business (related to deliveries), platform (related to the platform's capacity to process and allocate all requests), and ICT (related to the proper processing of all transactions).

- **Environmental Indicators**: These are used to measure the environmental effects of the shared system. They mainly focus on greenhouse gas emissions. There are multiple types of emissions, some natural, but the majority comes from human activities. The main ones are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and halogenated hydrocarbons (a group of gases containing fluorine, bromine, and chlorine). Among these, CO_2 is the most emitted gas. It is important to consider these emissions when evaluating the sustainability of different transportation modes (using carbon footprint). Additionally, the concept of water footprint, which measures the amount of water used to produce goods, should be integrated into the evaluation process to ensure a holistic approach to environmental impact assessment.

Based on these three mentioned criteria, we can consider a mono-objective optimization methodology that focuses on one of the three aforementioned indicators or a multi-objective optimization methodology that considers all of them.

5. Conclusions

In conclusion, this paper has presented a comprehensive review of simulation-based optimization and path planning algorithms in the context of supply chain management. The review highlighted the importance of these techniques in improving operational efficiency, reducing costs, and enhancing decision making processes. The study identified gaps in existing research, particularly in the integration of path planning algorithms in export distribution processes. To address these gaps, we proposed an approach that integrates advanced path planning algorithms into the transportation stage, specifically for export distribution via air or sea transport. This approach aims to optimize routes, schedules, and resources, ultimately leading to more efficient and sustainable supply chain operations. In the Future research should focus on implementing and evaluating the proposed approach in real-world supply chain scenarios to assess its effectiveness and practicality. Additionally, further investigation is needed to explore the potential integration of other emerging technologies, such as artificial intelligence and blockchain, in conjunction with simulation-based optimization and path planning algorithms. Overall, this paper contributes to the existing body of knowledge in supply chain management. It offers a novel approach that has the potential to revolutionize export distribution processes and drive significant improvements in supply chain performance.

Author Contributions

Y.B.J. wrote the manuscript in consultation with A.J. and M.H.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

No new data were created.

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