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A survey of supply chain management modeling and optimization: Key problems and recent solutions

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Abstract As a significant infrastructure of contemporary consumption and commodity production, supply chains formulate entire networks, from industrial production to sales. In recent years, several key challenges have emerged for supply chains, along with the rapid improvement in production capabilities and increased consumption, such as efficiency, robustness, and flexibility, among other concerns. To address these challenges, supply chains have been trending toward developing strongly interconnected networking structures and highly automated intelligent management. In the meantime, supply chain management (SCM) methods are increasingly being reshaped by artificial intelligence (AI)-driven decision-making techniques. This review provides a brief yet systematic survey of current modeling and optimization approaches for SCM. Specifically, we first introduce the fundamental decision-making problems in the four key areas of SCM, covering inventory management, logistics, production planning, and demand forecasting. We then review the classic and contemporary AI-driven methods employed to address these problems. Finally, we highlight some challenges and future research directions in the context of SCM.

Keywords supply chain management, optimization, inventory management, logistics, production planning, demand forecasting

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1 Introduction

The globalization process has fomented the widespread distribution of industrial production, transportation, and retail operations. With the advancements in the Internet and information technology (IT), the rise of e-commerce has established a more dynamic and fast-paced market [1, 2]. Consumers expect faster delivery times, personalized products, and seamless shopping experiences across multiple channels. Furthermore, emerging capabilities such as the industrial internet [3, 4], intelligent manufacturing [5, 6], and industry 4.0 [7, 8] are driving production and manufacturing sectors toward automation and intelligence. Supply chains are a bridge between industrial production and retail operations that coordinate suppliers, manufacturers, and distributors. An idealized supply chain must adapt to fluctuating consumer preferences and should also be capable of managing inventory in real time and ensuring seamless coordination across e-commerce and physical sales channels. Therefore, global supply chains' value has become especially pronounced, and the optimal design of efficient and flexible supply chains is a popular research topic [9–14].

Supply chains coordinate raw material suppliers and manufacturers on the upstream end and distributors and retailers on the downstream end. They maintain the flow of materials, funds, and information across associated enterprises, establishing stable, efficient, and sustainable industrial systems. Although supply chains within different fields are organized in diverse ways across different sectors, their general intent is to reduce the costs associated with procurement [15], production [16], transportation [17], and storage [18] processes. Beyond cost reduction, supply chains must ensure efficient logistics to maintain product quality and response time [19,20].

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The supply chain must be capable of withstanding market uncertainties or stochastic disruptions and reducing the possibility of extreme circumstances such as stockouts or backlogs. A well-organized supply chain can significantly enhance efficiency, reduce waste, boost profits, and stimulate economic growth.

Supply chain management (SCM) involves making optimal decisions based on available information to ensure the efficient flow of goods, services, and information from suppliers to consumers. Managers aim to determine the best strategies referencing their experience, computational simulations, and/or mathematical models to achieve objectives such as profit maximization. However, several challenges arise in managing a supply chain efficiently and cost-effectively. First, entities within the supply chain often belong to different organizations, and a tendency toward limited information sharing to protect individual interests can arise [21]. Such information asymmetry can impede a supply chain's ability to improve material flow efficiency and reduce overall competitiveness. Second, uncertainty within the supply chain hampers decision-making for all involved entities [14,22,23]. Uncertainties can arise from demand fluctuation [19], random events [24], and government policies [25], which make demand forecasting and production planning difficult and can result in lost sales, increased costs, and operational inefficiencies. Finally, the structure of modern supply chains has become significantly more complex due to globalization, technological advancements, and changing consumer expectations [26, 27]. The interconnection between different supply chain entities is strongly coupled and even dynamically changes with time [28–30]. Managing and optimizing such complex supply networks requires advanced strategies that ensure agility and flexibility.

Operations research, which provides systematic quantitative tools for solving complex decision-making supply chain problems, has a crucial role in SCM's development and optimization [31, 32]. A variety of optimization models have been developed for typical supply chain scenarios such as inventory management [33–41], logistics [42–46], and production [47–52]. These models can help managers make sound decisions to minimize costs, maximize service levels, and balance trade-offs between different objectives. Moreover, in recent years, technological advancements such as the Internet of Things (IoT) [53], blockchain [9] and artificial intelligence (AI) [37] have also introduced new approaches to SCM. These technologies have enabled enhanced data sharing, real-time visibility, and improved traceability, establishing more efficient, transparent, and responsive supply chains, which motivates our investigation of the latest developments in related fields.

This study provides a review of academic literature on SCM modeling and optimization, with a focus on fundamental challenges and recent AI-driven solutions. SCM encompasses a wide array of activities, such as materials procurement, product design, manufacturing, logistics, marketing, and retail. Considering the vastness and complexity of the field, it is challenging to offer an exhaustive review of all aspects of SCM. Consequently, our review specifically focuses on four critical areas: production planning during the production stage, inventory management during the intermediate stage, logistics during the distribution stage, and demand forecasting during the consumption stage. These areas form the core framework of SCM and provide a clear overview of its primary concerns. While this review concentrates on these key issues, it is crucial to acknowledge that other factors, such as marketing, purchasing and human resources, are also vital components of the broader supply chain and logistics ecosystem.

Several survey studies on SCM have been published in recent years [8, 11, 13, 21, 54]; however, these surveys primarily focused on the technical aspects of supply chain design. In contrast, this study provides a technical review of recent advancements in SCM from the perspective of modeling and optimization. Our goal is to explore how these innovations are transforming traditional operations research methods in SCM. Overall, the primary contribution of our review is twofold. First, it incorporates the latest advances in SCM modeling and optimization and can increase SCM practitioners' capability to leverage AI and machine learning (ML) technologies to persistent SCM challenges effectively. Furthermore, this review provides a rich framework of the real-world challenges faced in SCM that can help AI researchers understand the complexities and practical considerations that must be addressed when applying ML techniques in the supply chain field. Overall, this review bridges the gap between the practical challenges of complex SCM and the growing potential of AI advances to address these challenges.

2 Overview of supply chains and optimization models

2.1 Supply chain structure

A supply chain encompasses all processes involved in transforming raw materials into finished products and delivering them to end consumers, involving a series of interconnected activities such as sourcing, production, transportation, distribution, sales, and inventory management [55]. Figure 1 describes a typical supply chain diagram involving multiple entities such as suppliers, manufacturers, distributors, and retailers, wherein materials move downstream, while information and funds flow upstream. Suppliers deliver raw materials to manufacturers, who then produce products and pass them further downstream. Distributors are responsible for conveying products from manufacturers to retailers, and retailers handle the final sales stage. These processes facilitate

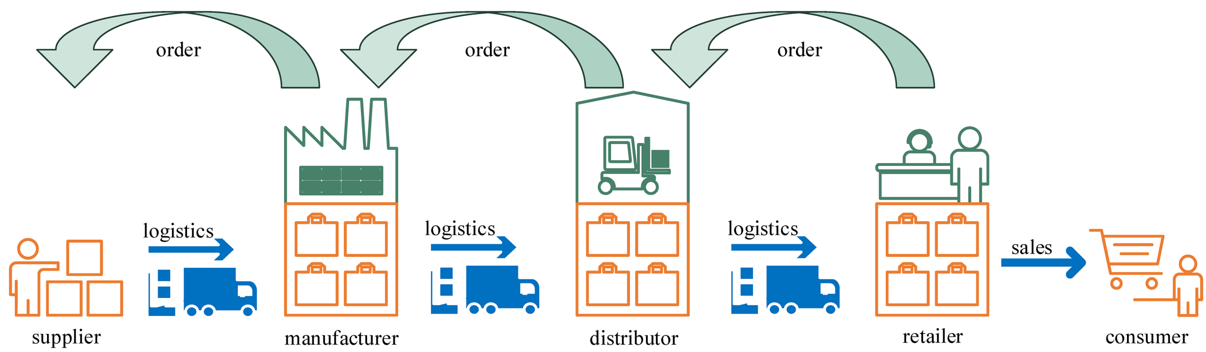

Figure 1 (Color online) Illustration of the supply chain structure.

the flow of materials, funds, and information to maintain supply chain operations.

Typically, a supply chain is represented as a chain [56] or network structure [27]. Contemporary supply chains may feature more complex structures, with multiple entities undertaking the same role, forming the supply chain network (SCN) [11]. This network structure enables the efficient flow of materials and information so that the right products are available at the right time and place to meet consumer demand.

Entities within a supply chain could be part of the same enterprise, but they are more frequently operated by different companies [15]. Intricate strategic interactions such as competition among these companies introduce difficulties in supply chain coordination [57]. Furthermore, products that flow across a supply chain often possess diverse attributes that impose various requirements on supply chain operations. For instance, perishable goods demand swift transportation across the supply chain to maintain quality, whereas products with a longer shelf life can accommodate inefficient logistics [58].

SCM encompasses multiple interconnected areas that collectively influence efficiency and competitiveness. Inventory management is a crucial component of SCM, as each entity within the supply chain must maintain an adequate buffer stock to ensure a continuous supply to downstream partners. The logistics process facilitates the movement of materials between entities and has a key role in determining the supply chain's overall efficiency. The factory production process is the starting point of product flow, and the costs associated with procurement and manufacturing have a significant impact on the overall competitiveness of the supply chain. Additionally, accurate demand forecasting is critical as it is inherently connected to inventory management, logistics, production, and other SCM processes. Considering the intrinsic delays in production and transportation, upstream entities must anticipate downstream demand to effectively align supply with customer needs. Accurate demand forecasting is vital for minimizing costs, enhancing risk resilience, and improving services throughout the supply chain [59].

Every operational procedure noted above contributes to the final retail cost of a product. Therefore, optimizing management strategies to reduce costs is a central focus of SCM. Various optimization techniques have been applied across different SCM areas to improve efficiency, reduce costs, and boost profitability. As noted above, this review focuses on four key areas of SCM: inventory management, logistics, manufacturing, and demand forecasting, which are fundamental to driving improvement and achieving cost-effective, streamlined operations throughout the supply chain.

2.2 Optimization models

The primary task of SCM is to ensure that products reach consumers in a timely manner, while each participant seeks to minimize costs and maximize profits. Consequently, optimization techniques are an integral aspect of SCM and are extensively applied to improve efficiency and profitability.

2.2.1 Basic optimization models

Mathematically, optimization is intended to identify the decision variable subject to certain constraints to maximize or minimize a specific objective function. A typical optimization problem can be expressed as follows:

$$\begin{aligned} \min \quad & f(\boldsymbol{x}), \\ \text{s.t.} \quad & g_i(\boldsymbol{x}) \leqslant 0, \ i = 1, 2, \cdots, m, \\ & h_j(\boldsymbol{x}) = 0, \ j = 1, 2, \cdots, n, \end{aligned}$$

where $\boldsymbol{x}$ is a scalar or multi-dimensional decision vector, $f(\cdot)$ is the objective function, and $g_i(\cdot)$ and $h_j(\cdot)$ respectively denote inequality and equality constraints.

Linear programming (LP) has been extensively studied and widely used for supply chain optimization problems, such as facility location and logistics planning [11, 55]. The objectives and constraints of LP problems are linear functions; therefore, the feasible region is a convex polytope and the solution is always located at the boundaries of this region. The simplex algorithm and interior point method are two typical approaches used to solve the LP problem, and many mature commercial or open-source solvers have been developed for LP problems.

Optimization problems involving nonlinear objective functions or constraints are referred to as nonlinear programming (NLP) problems. These types of problems are commonly applied in areas such as inventory management, demand forecasting, and commodity pricing [34, 60]. Considering that unconstrained convex optimization problems have been extensively studied, much more effort has been focused on how to transform constrained, nonconvex NLP problems into unconstrained convex problems. In this case, the Karush-Kuhn-Tucker (KKT) conditions provide necessary conditions for optimality in NLP problems. However, nonconvex optimization problems remain challenging, and only approximate solutions can be obtained for complex problems.

Some of the decision variables in supply chain problems, such as products' quantity and routing paths, could be discrete [11]. In this case, solutions based on the continuity assumption become infeasible in practice; therefore, these types of problems are typically modeled as discrete optimization problems (DOP), such as integer programming (IP) problems or mixed integer programming (MIP) problems. In many scenarios, these problems are commonly NP-hard and subsequently introduce significant computational challenges, especially in accommodating large solution spaces. Branch-and-bound and dynamic programming methods have commonly been employed for this type of problem-solving strategy [42, 44]. Problems with specific constraints, such as scheduling and routing, are typically classified as combinatorial optimization problems (COPs). While such problems can generally be formulated as IP or MIP models, specialized solution algorithms tailored to the unique structure of a problem have often been developed. Approximate methods such as heuristic algorithms and deep learning-based methods have frequently been employed to mitigate excessive computation, although this may come at the cost of solution accuracy [49].

In addition to cost metrics, factors such as service level, robustness, and environmental impact are often considered in SMC. As a result, multi-objective optimization problems (MOPs) are common challenges in this field [10]. A straightforward approach is to assign weights to each objective, which transforms the problem into a single-objective optimization. However, this method may not be suitable for all situations. An alternative is to assess multiple performance metrics using the concept of Pareto frontiers. This approach generates a set of optimal solutions that establish a hyperplane representing the optimal trade-offs among the various objectives.

2.2.2 *Advanced optimization problems*

Supply chain models may not always be deterministic, as random events are prevalent within SCM processes. Optimization and decision-making under uncertain conditions are significant topics in the SCM field. In such cases, stochastic programming (SP) problems are constructed, in which certain parameters are treated as random variables with specific probability distributions [24]. The optimization objectives are then adjusted to reflect specific statistical characteristics, such as the expected value and variance of residuals.

In comparison, robust optimization (RO) problems concentrate on preparing for the worst-case scenario, which can often be more intricate [12, 61]. In contrast, distributionally robust optimization (DRO) assumes that more distribution information is known outside the feasible domain, constructing an uncertain set of distributions to address the problem [62]. In many scenarios, entities must dynamically adapt to unknown external uncertainties by adjusting their strategies. These challenges are often modeled as Markov decision processes (MDPs). Recently, dynamic decision-making frameworks based on reinforcement learning (RL) and deep reinforcement learning (DRL) have gained considerable attention [16, 63]. Such algorithms can learn and adjust dynamically, using a predefined reward function to determine the optimal action at each step. Some studies have also employed optimal or robust control approaches to mitigate the effects of uncertainty [64]. The goal of optimal control is to determine the best sequence of control signals over a specified or infinite time horizon. This long-term, strategic approach helps maintain system stability, even in the face of unpredictable fluctuations.

A supply chain involves multiple companies with complex competitive and cooperative relationships. As a result, game optimization (GO) approaches have commonly been employed, in which other participants' actions are considered in decision-making [65–67]. Game theory is particularly useful in pricing strategy, especially for coordinating interactions between vendors and buyers [68]. This approach is a framework for understanding how different supply chain participants can influence one another's decisions and align strategies to achieve mutually beneficial outcomes.

As a brief summary, Table 1 details the commonly used

Table 1 (Color online) Common optimization problems in SCM

	Inventory	Logistics	Manufacturing	Forecasting
LP	–	✓	✓	–
NLP	✓	✓	–	✓
DOP	✓	✓	✓	–
MOP	✓	✓	✓	–
SP/RO	✓	✓	✓	✓
MDP	✓	✓	✓	✓
GO	✓	–	–	–

optimization models for inventory, logistics, manufacturing, and forecasting. We survey these models and associated optimization methods in detail in the next section. Notably, our survey primarily focuses on analytical modeling and optimization approaches; therefore, the simulation-based optimization approaches are not included in this review. Relevant studies include refs. [63, 69–71].

3 SCM modeling and optimization methods

This section presents a detailed survey of the SCM modeling and optimization from inventory management, logistics optimization, production planning, and demand forecasting perspectives.

3.1 Inventory management

An efficiently managed supply chain is expected to promptly meet market demand without shortages; however, as materials move downstream through the supply chain, time delays are inevitable during manufacturing and logistics. Therefore, inventory has a crucial role in supply chains to ensure the ability to fulfill service requirements. Effective inventory management is a critical SCM concern that is widely implemented within supply chains as a buffer against demand fluctuations and operational uncertainties.

As illustrated in Figure 2, the primary functions of inventory management can be divided into product distribution according to downstream orders and upstream orders based on current inventory levels and future demand. Beyond simply meeting downstream entities' demand, managers also aim to minimize overall inventory costs while maintaining stock levels. Therefore, companies can improve financial performance by implementing optimal replenishment strategies that strike a balance between the costs of stockouts and inventory holding.

3.1.1 Basic inventory models

The economic order quantity (EOQ) model, introduced by Harris [72] in 1913, is a foundational approach for continuously reviewed inventory systems. In this model, the replenishment process assumes zero lead time and constitutes an idealized framework. Furthermore, inventory levels are assumed to decrease linearly over time with constant and known demand. Once inventory reaches zero, it is immediately replenished to order quantity Q by placing a new order, which is calculated to minimize the total costs associated with holding inventory and ordering new stock over a given period. The total cost is commonly represented as

$$C(Q) = \frac{h}{2}Q + k\frac{D}{Q} + cD. \quad (1)$$

In this model, h is the coefficient of holding cost, k is the coefficient of the fixed cost of a single order, c is the coefficient of variable order cost, and the demand rate D is constant. The primary intent of the replenishment strategy is to determine the time points and/or order quantities that optimize the total cost $C(Q)$. Eq. (1) is a convex function with optimal order quantity $Q^* = \sqrt{\frac{2kD}{h}}$. Managers often maintain a buffer stock to ensure that demand is promptly met, whereas holding excess inventory could also result in capital loss due to inefficiencies. When the costs of shortages can be quantified, managers may factor them into penalty costs as an aspect of their total cost considerations. Managers may adopt a zero-inventory strategy for products with low demand or high holding costs to avoid unnecessary holding or potential sunk costs. This approach, which is known as the just-in-time (JIT) strategy, involves ordering only when immediate need arises [24].

In contrast, the EOQ model is a simplified framework that does not fully capture the complexities of real-world inventory management. In practice, orders must be placed before inventory is depleted to account for lead time (i.e., the period between placing an order and receiving the materials). Managers typically maintain a certain level of safety stock to prevent stockouts during replenishment. This (r, Q) policy that immediately orders a predetermined quantity Q when the inventory decreases to the established reorder point r is widely adopted for continuously reviewed products [33, 73]. The reorder point r should exceed the safe inventory level to cover demand during the reorder process. The (s, S) policy that replenishes the inventory level up to S if the on-hand inventory falls below s was found to be more suitable for periodically reviewed inventory systems [35]. More specific models can be found in ref. [60].

Depending on the specific product category, managers must consider various factors such as lead time, safety stock, transportation capacity, and production rates. In practice, actual inventory management strategies may be customized variations of these basic models. Managers typically use optimization techniques that are formulated as NLP or MIP problems to determine optimal order times and quantities.

Products' prices can affect consumers' willingness to purchase, particularly for goods with elastic demand and inventory management is closely aligned with pricing strategies in such circumstances. Combining dynamic pricing with inventory control can be a powerful approach to enhance profitability [36]. In addition, pricing strategies also involve factors of cooperation, competition, and fairness concerns across different sales channels [15].

Perishables such as fresh goods and blood products are commonly encountered in daily life. Such items have limited shelf lives [38] or are subject to gradual degradation over time [39]. Holding large quantities of perishable goods is

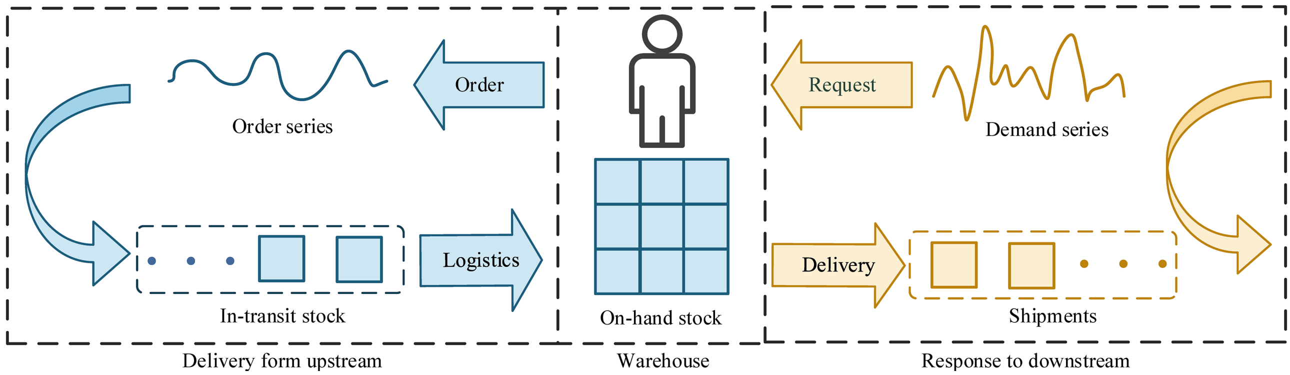

Figure 2 (Color online) An illustration of inventory management procedure.

prone to considerable losses, and such products generally require lower inventory levels and more efficient logistics operations. Therefore, the perishable goods supply chain is particularly vulnerable to market fluctuations [40].

3.1.2 Stochastic inventory management

SCM processes often involve uncertainty and variability that must be modeled probabilistically rather than deterministically. Uncertainties arising from demand fluctuations, variable lead times, and unreliable supply channels can significantly impact inventory management, potentially resulting in stockouts and other challenging scenarios. Therefore, stochastic modeling is commonly used in such scenarios to account for variability and optimize decisions concerning order quantities, stock levels, and safety inventory.

The newsvendor model is a classic framework for determining the optimal order quantity Q over a single period at which demand D is a stochastic variable that follows a specific probability distribution $\mathcal{P}$ [34]. The basic model is particularly relevant for products with discrete order quantities in which unsold items can be returned or recycled. Expected earnings are calculated by considering the revenue from sales and costs of order and unsold inventory as follows:

$$C(Q) = p\mathbb{E}\left[\min(Q, D)\right] + s\mathbb{E}\left[\max(Q - D, 0)\right] - cQ,$$

where the coefficients p, s, and c denote the selling price, the salvage price, and the unit order cost, respectively. The form of the profit function $C(Q)$ is shaped by the distribution of D and typically results in an NLP or MIP problem.

In some cases, the distribution of random variables is poorly understood, and profit maximization may not be the sole objective. Instead, inventory management might prioritize maintaining service levels under conditions of extreme uncertainty. In this scenario, some reduction in profit is accepted in exchange for improving the inventory system's robustness. For example, in the newsvendor problem, where only the feasible demand region $\mathcal{D}$ is known, the goal of robust optimization is to maximize profit in the worst-case scenario as follows:

$$C(Q) = \max_{Q} \min_{D \in \mathcal{D}} \left[p \min(Q, D) + s \max(Q - D, 0) - cQ\right].$$

In addition to demand uncertainty, supply channel variability can also affect inventory stability. Fluctuating lead times due to changes in production and logistics can potentially accelerate or delay deliveries [37]. Moreover, supply quantities may decrease or even cease entirely if stockouts in upstream sources occur [74].

Note that many inventory management problems involve nonconvex objective functions and high-dimensional decision variables, which makes them difficult to solve using analytical approaches [75]. As a result, heuristic [37] and metaheuristic [76] techniques are often employed to address these complex issues. Moreover, robust optimization is a semi-infinite optimization problem that presents further computational challenges. To address these concerns, control theory-based methods have also been adopted that use robust control approaches to balance system stability and optimality [39].

3.1.3 Multi-echelon inventory system

While inventory management models often focus on a single entity, real-world systems are typically organized as multi-echelon chain structures. In many cases, downstream entities adopt multi-vendor strategies to mitigate the impact of supply disruptions, contributing to an increasingly complicated supply chain structure [18]. It is essential to recognize that the optimal decision for each individual entity does not inherently lead to an overall supply chain optimum.

When suppliers manage the overall inventory in a supply chain through vendor managed inventory (VMI) systems [77], the goal is to optimize total inventory costs across all entities. However, as the number of nodes in the supply chain increases, the number of decision variables also expands, introducing computation difficulties [78]. A more practical approach is to foster cooperation between entities, which can be achieved by establishing procurement contracts between upstream and downstream entities to secure a mutually beneficial strategy [57]. Alternatively, it is also feasible to maintain limited information sharing between entities to enhance the supply chain's overall efficiency and effectiveness [56].

The bullwhip effect is a common phenomenon wherein fluctuations in demand are amplified as they move upstream along the supply chain. In addition to demand fluctuations, information asymmetry and entities' self-interest decisions were determined to be the main causes of the bullwhip effect [79]. One effective way to reduce the bullwhip effect is to forgo a portion of each entity's benefits in exchange for information sharing via VMI, which shifts the focus from individual optimization to system-wide optimization [80]. However, considering that only limited cooperation between entities is possible, it is challenging to fully adopt this approach. As a result, various distributed inventory strategies have been designed and tested. In particular, optimal control approaches [39, 81, 82] have been shown to be effective in mitigating the bullwhip effect by reducing order fluctuations.

3.1.4 Deep learning methods for inventory management

In recent years, deep learning methods have increasingly been applied to inventory management to improve efficiency, forecasting accuracy, and decision-making. These methods employ complex neural networks to analyze vast amounts of data, identify patterns, and make predictions regarding inventory needs and demand fluctuation. Considering its ability to address complexity optimization problems, deep learning offers a new approach for addressing inventory management problems [83].

Specifically, since inventory management is a dynamic decision-making process that must continuously adapt to market changes, managers' decisions are often influenced by on-hand stock, in-transit stock, and expected demand. Therefore, some studies have treated inventory management problems as MDPs and introduced DRL to seek near-optimal strategies within the changing environment [84–86]. For instance, ref. [87] used transfer learning methods to train DRL models based on the heuristic method for efficient and low-cost management of perishable products. Moreover, some DRL-based game models have been proposed for inventory management scenarios to coordinate order strategies between different entities, increase profits, and mitigate the bullwhip effect [68].

Another significant advantage of deep learning is its ability to make informed decisions using data. These data-driven methods are often combined with demand forecasting [88]. Ref. [89] employed an end-to-end framework to help manage the replenishment process for an e-commerce platform. The proposed deep learning approach can learn the optimal strategy directly from the data, and has achieved favorable results in industrial practice. It can also assist inventory managers by predicting supplier performance and identifying potential disruptions. However, these methods require large, high-quality datasets to produce accurate predictions. Moreover, the convergence and robustness of DRL approaches remain a key challenge for further research.

3.2 Logistics optimization

As shown in Figure 3, logistics systems facilitate the transportation of materials across various entities within the SCN. Logistics' efficiency has a substantial influence on how quickly the supply chain can respond to demand fluctuations. Furthermore, logistics costs frequently represent a substantial share of total supply chain expenses and can be the predominant cost. Therefore, optimizing logistics operations is a critical aspect of comprehensive supply chain optimization strategies.

Logistics optimization can be categorized into strategic, tactical and operational planning according to the length of the associated time horizon. This section explores optimization issues in the logistics domain with a focus on strategic logistics network design, tactical channel allocation, and operational route planning and warehousing. Notably, these areas are not completely separate, as a logistics decision problem may consider long-, medium-, and short-term models simultaneously.

3.2.1 Logistics network design

Logistics networks' design and layout are fundamental tasks in the early stages of supply chain development and can have a lasting impact on subsequent SMC operations for several years or more. The location layout problem is a foundational issue in logistics network design that involves identifying the optimal node locations to minimize the supply chains' operational costs and maximize profits.

This problem is often modeled as a mixed-integer linear programming (MILP) or a mixed-integer nonlinear

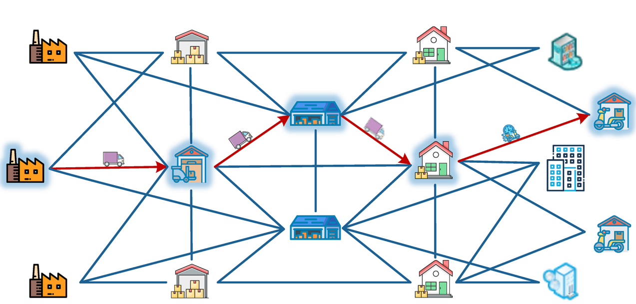

Figure 3 (Color online) An illustration of logistics within a supply chain network.

programming (MINLP) problem with the following universal representation:

$$\begin{aligned} \min \quad & f(x_1, x_2, \cdots, x_m), \\ \text{s.t.} \quad & g_i(x_1, x_2, \cdots, x_m) \leqslant 0, \ i = 1, 2, \cdots, n, \\ & x_k \in \mathbb{Z}, \ \text{for some } k \in \{1, 2, \cdots, m\}, \end{aligned}$$

where the notion $\mathbb{Z}$ is the integer set, meaning that some elements of the decision vector x are integers. The cost function $f(x)$ can involve a variety of expenses, such as initial construction costs, production and procurement expenses, logistics fees, environmental impact, and potential costs from supply chain disruptions [11]. Moreover, constraints $g_i(\cdot)$ are primarily derived from physical limitations such as supply and logistics capabilities. These models may also be presented as multi-objective optimization problems to balance different performance metrics [13].

Uncertainty is a core challenge in supply chain design. Addressing these uncertainties is crucial for preventing potential failures due to unforeseen events. To this end, stochastic and robust optimization models have been integrated into the logistics network design processes [14]. For example, the study [12] considered an actual case of a bread supply chain with uncertain demand and varying costs, proposing a robust optimization model to determine prime locations and allocations. Uncertainty concerns motivate companies to consider real-world risks to avoid the pitfalls of overly idealized models.

Some studies have also focused on adapting the existing logistics network to better handle disruptions. Furthermore, a growing body of literature has examined failed supply chains' operational recovery [90]. Notably, identifying a precise solution can be challenging for the design of large-scale logistics networks due to the "curse of dimensionality" [55]; therefore, the majority of the existing literature has relied on heuristic or metaheuristic algorithms to effectively solve large-scale MIP problems [91].

3.2.2 Transportation optimization

Once a logistics network is operational, the focus shifts to products' daily transportation. Commodity transportation within the SCN primarily involves route selection and vehicle allocation, and most of these scenarios can be expressed as LP or MILP problems.

The transportation problem (TP) is a key mid-term channel allocation issue to determine the most efficient strategy for transporting materials from multiple suppliers to various customers. In a classic TP, the total amount of supply matches the total demand, and the objective is to minimize overall costs by assigning the most efficient traffic volumes to each edge within the network. The TP can be modeled as the following standard LP problem:

$$\begin{aligned} \min \quad & \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}, \\ \text{s.t.} \quad & \sum_{i=1}^{m} x_{ij} = a_i, \ \sum_{j=1}^{n} x_{ij} = b_j, \\ & x_{ij} \geqslant 0, \end{aligned}$$

where i denotes the supplier and with a total number of m, j denotes the receiver with a total amount of n. c_{ij} denotes the cost coefficient, and the decision variable x_{ij} represents the volume of transportation, referring to the number of goods transported along each route. The constraints in the TP model reflect the supply capacities of the originating node i as a_i and the demand requirements of the destination node j as b_j, which depend on supply and demand at each node and the transportation capacities of the routes connecting them.

In ref. [92], the simplex method is first applied to solve TP. However, heuristic algorithms often outperform traditional methods in terms of computation time for large-scale problems. Therefore, algorithms such as the simulated annealing algorithm (SA), genetic algorithm (GA), and the ant colony algorithm (ACO) have gained popularity due to their efficiency [58].

The key to solving the TP is achieving a balanced flow of goods within the SCN in which the total inflow equals the total outflow at each node. Such problems are often addressed in terms of network flow theory, which calculates the maximum flow or minimum-cost maximum-flow based on the network topology. Well-known algorithms in this area include the Ford-Fulkerson algorithm, the Edmonds-Karp algorithm, and the Dinic algorithm [93], which were designed on the basis of network flow theory and are more explanatory. In particular, an unbalanced TP in which total production is unequal to sales can be extended to a standard TP by introducing a virtual production or demand node.

Multimodal transportation is a common approach to balance efficiency, cost, and risk [94]. This method extends the traditional TP by incorporating rail, water, road, and air transport modes. Goods flow through the SCN via these modes in parallel or in series. The complexity of this problem is amplified by the inherent capacity constraints and time window limitations in each mode of transport making the multimodal TP more challenging than the standard TP.

3.2.3 Vehicle routing optimization

The vehicle routing problem (VRP) is a classic COP in which the decision space is a discrete set with special topological constraints. VRPs are more general optimization tasks that focus on minimizing total delivery time or logistics costs.

Recent studies have also integrated environmental considerations, such as reducing congestion to reduce carbon emissions [22]. Unlike TPs, VRPs require accounting for the topological relationships between nodes and considering additional constraints such as vehicle capacity and time windows.

A general VRP considers scheduling multiple vehicles to minimize the total cost of all vehicles in the system. Denote m and n as the number of vehicles and the number of destinations, respectively. The mathematical formulation for considering topological constraints is as follows:

$$\begin{aligned} \min \quad & \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} c_{ij}x_{ij}^{k}, \\ \text{s.t.} \quad & \sum_{j=1}^{n} x_{0j}^{k} = 1,\ \sum_{i=1}^{n} x_{i0}^{k} = 1,\ \forall k = 1, \cdots, m, \\ & \sum_{k=1}^{m}\sum_{j=1}^{n} x_{ij}^{k} = 1,\ \forall i = 1, \cdots, n, \\ & x_{ij}^{k} \in \{0, 1\}. \end{aligned}$$

Here, the decision variable $x_{ij}^{k} = 1$ if vehicle k chooses the path $i \rightarrow j$, and $x_{ij}^{k} = 0$ otherwise.

The basic models of path planning are the shortest path problem (SPP) and traveling salesman problem (TSP) that identify the optimal route within a graph to minimize the sum of the edge weights between two nodes. SPP can be addressed within polynomial time using dynamic programming, the Dijkstra algorithm, and the A^* algorithm, while TSP is NP-hard and large-scale instances can only be efficiently solved using approximate methods.

Section 2.2 cited the use of branch-and-bound, cutting-plane, and dynamic programming methods to search for the solution within an acceptable time for small-scale problems. However, in reality, VRPs often include a large number of nodes and must account for a variety of constraints, such as maximum cargo volume, delivery time windows, road restrictions, and dynamic demand [42]. To accommodate the typically exponential computational complexity of VRPs, heuristic algorithms have commonly been used to search for near-optimal solutions [17, 95].

In practice, path planning must consider various constraints, resulting in different types of VRPs. These include the capacitated VRP (CVRP) with a focus on capacity limitations; VRP with time windows (VRPTW), which incorporates time constraints; the heterogeneous VRP (HVRP) that can accommodate a mix of different vehicle types; and the dynamic VRP (DVRP), which includes real-time planning [42, 44–46]. Products' transportation must also factor in the effects of uncertainties that can disrupt preplanned schedules, such as traffic congestion, weather conditions, and vehicle breakdowns. These challenges are often addressed through robust optimization models, which add to the complexity of solving such problems. Ref. [62] introduced a distributionally robust optimization model to simplify TSP with time windows (TSPTW).

3.2.4 Warehousing and picking

Warehousing and picking are integral to the beginning and end of transportation processes, with some transportation workflows also involving terminal operations. The primary goal of optimizing these processes is to efficiently schedule equipment and manual labor, such as selecting optimal job paths to minimize total time and maximize resource use [96]. For example, in warehouse picking, the focus is typically on reducing the total picking time or travel distance, while terminal operations aim to improve efficiency by minimizing loading and transit times. These challenges share similar mathematical formulations with VRPs with key differences in decision variables and constraints. In warehouse picking tasks, constraints include vehicle loading capacity, completing pick-ups, and maintaining continuous paths. In terminal operations, constraints often involve operational time windows to ensure efficient use of equipment.

Traditionally, these problems are addressed by exact optimization techniques. For example, ref. [96] employed a commercial solver to address the warehouse picking problem, demonstrating its practical application for improving pick rates per employee and ensuring equitable workload distribution. However, obtaining a precise solution can be challenging for problems with complex constraints and high dimensionality, and the quality of approximate solutions must be carefully evaluated. The advent of IoT technology has resulted in a rise in process simulations that can be integrated with optimization approaches to assess the quality of the derived solutions [97].

3.2.5 New technologies for logistics optimization

Optimization problems that correspond to network design and path planning often encounter the challenge of the "curse of dimensionality" and the complexity of constraints. In addition to heuristic solutions, ML approaches have also demonstrated promising potential for addressing design problems [98] and VRPs [99].

Given the topological considerations and inherent geographical relationships between nodes in path planning problems, VRP solutions based on graph neural networks (GNNs) [100] and Transformer models [101] have emerged as a prominent research focus. The strength of deep learning is its generalizability, i.e., a pre-trained model that has learned a prior paradigm for problems with similar structures has a higher computational efficiency and can produce better results. Ref. [100] presented an example of a GNN-based order scheduling approach and demonstrated its validity using a real data set collected from a delivery platform. In addition to the end-to-end approach [102], deep learning can also be combined with heuristic algorithms for training or joint solutions for improved performance [103], and reinforcement learning methods are often applied when training these models. Furthermore, logistics processes frequently involve random events, dynamic demands, and changing environments that necessitate vehicles to dynamically adapt previously planned routes accordingly. To address these challenges, DRL approaches have also been introduced to obtain online solutions [104, 105].

In recent years, a growing interest in developing more flexible transportation modes has emerged. In particular, electric vehicles (EVs) have attracted increased attention due to their potential to reduce carbon emissions, which aligns with the current focus on environmental costs in SCM [45,104]. However, EVs' limited battery life and the accessibility of charging stations present a significant challenge in route planning and the potential impact on travel time [46].

Moreover, the advent of autonomous driving technology has also sparked interest in unmanned logistics vehicles. Alternative logistics methods such as unmanned aerial vehicles (UAVs) and autonomous vehicles, are gaining traction for their potential to minimize human labor dependence and expedite delivery services [106, 107]. In addition, the application of automated guided vehicles (AGVs) and collaborative robots has greatly improved warehouse management efficiency. These technological innovations are poised to revolutionize the logistics sector by boosting operational efficiency and reducing the environmental footprint.

3.3 Production management

Manufacturing facilities upstream in the supply chain have a pivotal influence on retail pricing and overall supply chain performance. Producers craft production plans in response to downstream demand through direct orders and/or market forecasts. Efficient planning is essential to prevent delivery delays and maintain inventory levels at a minimum, as emphasized by the criticality of JIT production strategies. Concurrently, streamlining the production process can markedly enhance resource utilization and manufacturing efficiency. This section examines the optimization challenges within the production process with a focus on strategic production planning and operational scheduling.

3.3.1 Production planning

Manufacturers must develop production plans that align with their production capacity to ensure the timely fulfillment of downstream demand. Production planning typically spans a longer time horizon, ranging from weeks to months, to optimize resource utilization and improve overall production efficiency.

As a complex and multifaceted problem, production planning varies between industries and regions, with different companies prioritizing distinct concerns. In addition to managing raw materials and finished goods inventories, a crucial concern of production planning is strategic resource allocation, including equipment and personnel. No one-size-fits-all model exists for production planning. Companies often rely on tailored optimization models to guide their strategies, sometimes even using manual solutions. Enterprise production planning (ERP) systems are commonly used to manage these challenges by framing production problems as LP or MIP models and employing optimization software to determine a solution [108]. In some cases, heuristic algorithms and simulation-based approaches are employed to find near-optimal solutions.

Given the inherent lengthy lead times in production processes, including material procurement and resource allocation, manufacturing enterprises often struggle to swiftly respond to substantial shifts in demand. Consequently, these companies typically rely on existing downstream orders or engage in forecasting to anticipate future demand. Therefore, it is crucial to integrate demand forecasting and production scheduling [109]. Precise demand forecasts are instrumental in enhancing the effectiveness of production planning by aligning manufacturing activities more closely with market demand.

3.3.2 Production scheduling

Adept production resource scheduling is crucial for significantly boosting production process efficiency. Optimization goals include reducing overall production time, maximizing equipment use, enhancing process reliability, and minimizing raw material use. The production process is frequently constrained by the machinery's processing capacity and the availability of raw materials. Addressing these challenges often involves formulating integer programming problems, with decision variables centered on the sequencing of workpieces across production stages. In practice, production scheduling is usually handled by manufacturing execution system (MES) software.

Single machine scheduling [47] and parallel machine scheduling [48] problems represent two fundamental issues within the realm of production scheduling. The primary objective in these scenarios is typically to minimize total processing time. For example, in the context of a parallel machine scheduling problem, denote i as the index of machines and j as the index of jobs. The challenge is to allocate jobs to machines to minimize the maximum load on any machine, as discussed in ref. [48]. Its mathematical formulation can be written as follows:

$$\begin{aligned}
\min \quad & C_{\max} = \max_{j=1,\cdots,n} C_j, \\
\text{s.t.} \quad & \sum_{i=1}^{m} x_{ij} = 1,\ 1 \leqslant j \leqslant n, \\
& \sum_{j=1}^{n} p_j x_{ij} \leqslant C_{\max},\ 1 \leqslant i \leqslant m, \\
& x_{ij} \in \{0, 1\},
\end{aligned}$$

where p_j and C_j denote respectively the processing time and actual completion time of job j, and $x_{ij} = 1$ if job j is assigned to machine i.

Furthermore, the various production processes of products result in highly diverse workshops. Large quantities of a single product are typically produced in a flow shop [50], where production follows a defined sequence of operations. In contrast, small batches of multi-variety products are usually produced in a job shop [51], where each product may require different equipment or follow distinct but specific procedures, as shown in Figure 4. A workshop without fixed process constraints is referred to as an open shop.

Similar to VRPs, small-scale scheduling problems can be solved using exact methods such as dynamic programming [110] or branch-and-bound methods. Notably, some studies have developed optimal control approaches based on the principle of maximizing value to achieve multi-objective and multi-level scheduling in intelligent factories [111]. However, most shop scheduling problems are NP-hard; therefore, only approximate solutions can typically be obtained for large-scale scheduling problems using heuristic algorithms [112, 113].

Modern production lines must also be adaptable to the impact of uncertain factors, such as machine failures, labor shortages, and new job arrivals [114]. For example, ref. [115] proposed a multi-objective particle swarm optimization to achieve stable scheduling under dynamic events. Load balancing is often incorporated into scheduling problems to mitigate the risk of machine breakdowns. In addition, production lines should also have the ability to dynamically adjust to cope with inserted tasks or emergencies [53]. In some studies, shop scheduling problems have been modeled as dynamic decision-making problems for rapid response [116, 117].

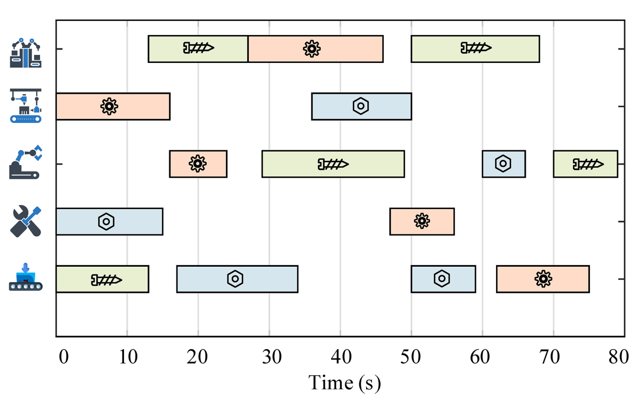

Figure 4 (Color online) Gantt chart of a job shop scheduling. The horizontal coordinate is the time epoch, while the vertical coordinate is the machine used in different processes. The blocks with bolt, gear, and nut represent three different workpieces, respectively.

3.3.3 *Machine learning methods for production management*

With rapid advances in robotics and IT, smart factories have emerged as a leading trend in manufacturing [118]. Modern smart factories introduce automated handling robots, human-robot interaction systems, and other automated tools to replace or assist workers [119, 120]. Using these automated tools can further enhance the production flexibility and intensify the complexity of scheduling problems. In particular, a problem concerning a job shop with parallel machines, which is known as the flexible job-shop scheduling problem (FJSP), poses significant challenges and is a highly investigated topic [115]. As a typical COP similar to VRPs, a high-dimensional FJSP can only be solved using an approximate method. Ref. [52] proposed a heuristic algorithm to solve this problem, which was applied to real production scenarios for validation. Moreover, deep neural network (DNN) models and DRL methods have exhibited substantial potential in efficiently addressing complex FJSPs [16, 20, 48, 121].

While production planning and production scheduling are often treated separately in practice, to improve overall production efficiency, it is imperative to consider these two processes holistically by integrating ERP software with MES [122]. Furthermore, the fast-moving consumer goods (FMCG) industry has achieved overall optimization of the supply chain profit by integrating production, logistics, sales, and other processes. This technique could be widely adopted across various industries to achieve comprehensive supply chain coordination.

3.4 Demand forecasting

Demand forecasting has a critical influence on SCM, as it directly impacts decision-making in various supply chain stages. Accurate demand prediction can enable businesses to optimize inventory levels, production schedules, and procurement strategies, reducing inefficiencies and costs. Market demand is influenced by numerous factors, including market trends, seasonality, external events, and correlations with other products (Figure 5). Therefore, future demand is inherently uncertain and often difficult to predict with precise accuracy. The goal of demand forecasting is to identify pat-

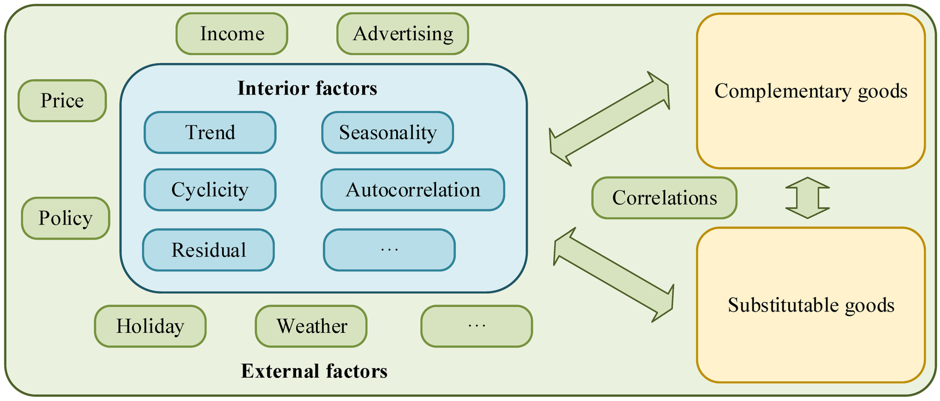

Figure 5 (Color online) The influencing factors of demand. The blue blocks represent features of time series, the green blocks are external influencing factors, and the orange blocks indicate correlations with complementary and substitutable products.

terns and trends within this uncertainty that can help guide more informed decision-making.

SCM forecasting methods can be broadly classified into qualitative and quantitative approaches. Qualitative forecasting methods rely substantially on managers' intuition and judgment and are less precise and harder to quantify in terms of accuracy, whereas quantitative forecasting uses historical data and statistical models to forecast future demand. In this section, we primarily concentrate on quantitative forecasting methods to offer more measurable outcomes.

3.4.1 Time series forecasting

Demand forecasting commonly involves examining patterns from a time series of historical demand data. The aim of time series forecasting (TSF) is to identify demand trends, periodic patterns, and autocorrelations within the data series to extrapolate insights for predicting future demand. Essentially, TSF entails fitting a function that captures key trends in the historical data while minimizing the risk of overfitting to ensure its generalization to future periods.

One strategy to mitigate overfitting is to select an appropriately simple model with a low order. The exponential smoothing (ES) model [123] is commonly used to predict future demand $\hat{D}$ as a weighted sum of past demand D. Specifically, the basic ES model can be iteratively formulated as follows:

$$\hat{D}_{t+1} = \alpha D_t + (1-\alpha)\hat{D}_t, \quad t = 1, 2, \cdots,$$

where $\alpha \in (0,1)$ is an adjustable coefficient, and the t subscpript denotes the time epoch.

Since D is a random variable, the optimization target aligns the model parameter α to minimize statistical metrics such as mean absolute error (MAE) or root mean squared error (RMSE), which are NLP problems. The averaging process in ES filters out high-frequency noise from the data to effectively capture the predictable elements of demand. The ES model is well suited for stationary processes, yet it struggles to capture demand that exhibits trends or seasonality. To address this limitation, Holt [124] and Winters [125] extended the ES model to higher orders to better accommodate trends and seasonal fluctuations. However, the choice of models is still subject to managers' the judgment.

Another approach to demand forecasting is regression analysis of stationary data. An important feature of the demand sequence is autocorrelation in which the current demand is correlated with the previous demand. The autoregressive (AR) model treats predictions by weighting historical data D_t. In contrast, the moving average (MA) model treats predictions as a weighting of historical residuals ε_t. The autoregressive integrated moving average (ARIMA) model [126] integrates these two models and introduces differential treatment of nonstationary sequences. p, d and q respectively denote the order of the AR model, the difference, and the MA model, and an ARIMA(p,d,q) model can be represented as follows:

$$\begin{aligned} D_t^d =& c + \phi_1 D_{t-1}^d + \phi_2 D_{t-2}^d + \cdots + \phi_p D_{t-p}^d \\ &+ \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}, \end{aligned}$$

where $\phi_1, \phi_2, \cdots, \phi_p$ are the coefficients of AR model and $\theta_1, \theta_2, \cdots, \theta_q$ are the coefficients of MA model.

Nevertheless, this model requires the data to satisfy certain assumptions of stationarity, and in some cases, the original data can be transformed to improve processing [127]. Hence, appropriate (p,d,q) order parameters should be chosen to meet the stationarity requirements and estimate the model parameters (ϕ_i, θ_j). Akaike information criterion (AIC) and Bayesian information criterion (BIC) are frequently employed to address this issue [128]. Their criteria incorporate a penalty term for the number of parameters in the likelihood function to prevent overfitting.

Parameter estimation challenges are typically framed as

NLP issues. Maximum likelihood estimation (MLE) and least squares (LS) methods have been the most commonly used approaches. The MLE method maximizes the possibility $L(\boldsymbol{\phi}, \boldsymbol{\theta})$, while the LS method minimizes the second moment of the residual $S(\boldsymbol{\phi}, \boldsymbol{\theta})$, where $\boldsymbol{\phi} = [\phi_1, \phi_2, \cdots, \phi_p]^{\mathrm{T}}$, $\boldsymbol{\theta} = [\theta_1, \theta_2, \cdots, \theta_q]^{\mathrm{T}}$, respectively.

The ARIMA model and its variants have been widely used in demand forecasting [59]. In addition, the generalized autoregressive conditional heteroskedasticity (GARCH) model captures changes in conditional heteroskedasticity within the data, relaxing the assumption of constant variance that is inherent to the ARIMA model [129]. However, both of these forecasting methods still rely heavily on expert judgment for model selection and tuning. Ref. [130] adopted a curve-fitting approach to produce long-term predictions that account for trends and seasonal variations, which incorporates the Fourier series to model periodic components of the data.

3.4.2 Multiple regression and multivariate time series

As discussed previously, TSF methods focus on modeling the average, trend, seasonality, and autocorrelations within the data over time; however, as illustrated in Figure 5, future demand is influenced by various external factors, such as price, weather, and resident incomes. The autoregressive integrated moving average with exogenous inputs (ARIMAX) model [131] extends the ARIMA framework by integrating these exogenous variables, which are closely related to demand, to improve forecasting precision. The modeling and forecasting processes of ARIMAX are similar to those of the standard ARIMA model. Similarly, the Prophet model [130] also incorporates factors such as holidays and other external inputs to refine the performance of the model.

In some cases, companies must forecast multiple time series simultaneously, and correlations may exist between them. For example, sales of complementary or competing products often influence one another, and accounting for these interdependencies can produce more accurate forecasts. TSF models such as ES, AR, MA, and ARIMA can be extended to multivariate versions to handle such scenarios, where variables are treated as vectors that include demand and related influencing factors [132].

The parameter estimation process for multivariate time series forecasting (MTSF) is similar to the approach used for univariate time series; however, MTSF models can suffer from multicollinearity in which high correlations between multiple variables can distort the model's estimations. Principal component analysis (PCA) can be used to reduce collinearity by removing some of the correlated variables. In addition, incorporating regularization terms into the loss function can help mitigate the effects of collinearity and yield more stable regression coefficients [133]. Common regularization techniques include ridge regression and LASSO regression.

3.4.3 Machine learning methods for demand forecasting

Linear regression models often struggle to capture the complex relationships between demand and its various influencing factors. With contemporary IT advances, supply chains can now access data more easily, which makes it possible to extract valuable insights directly from large datasets. As a result, ML techniques are increasingly being adopted for complex demand forecasting scenarios, offering a more effective approach to generate automated SCM strategies [59].

Specifically, ML methods such as support vector regression (SVR) can capture complex, nonlinear patterns in data by employing various kernel functions. Decision tree (DT) algorithms, which rely on information entropy, have also been found effective for analyzing the impact of multiple factors on demand. Improved DT algorithms such as random forest, XGBoost, and LightGBM have gained widespread adoption in demand forecasting due to their ability to accommodate large datasets, reduce overfitting, and improve prediction accuracy [134].

In particular, deep learning has become a prominent focus in demand forecasting in recent years [135]. For example, recurrent neural networks (RNNs) are well suited for TSF as they can capture dependencies within sequential data. Ref. [136] applied an integrated ARIMA and RNN method to a semiconductor distributor's the demand forecasting and demonstrated good performance. In contrast, the long short-term memory (LSTM) model [137] offers significant advantages in handling data with causal relationships. Other models such as convolutional neural networks (CNNs), GNNs, and Transformer-based architectures have also been introduced to enhance forecast accuracy and interpretability [138, 139].

Considering that demand data are continuously obtained during the supply chain operation process, a growing interest in developing online forecasting methods has emerged. DRL has been widely used for demand forecasting and inventory management strategies as it can iteratively refine strategies in response to market fluctuations and has significant advantages in terms of adaptability [140]. Furthermore, deep learning-based anomaly detection [141, 142] and sentiment analysis are also employed to enhance the quality of forecasts.

Deep learning methods have demonstrated potential and scalability in demand forecasting; however, it must be noted that the current body of research has not sufficiently validated these techniques to render traditional forecasting models obsolete. In fact, the effectiveness of ML methods remains questionable, and sometimes, their predictions do not outperform those of traditional methods. Therefore, significant room remains for the integration of deep learning approaches with existing methods within the field.

4 Trends and future perspectives

Technological advances like the IoT have promoted demand forecasting considerably and significantly enhanced SCM capabilities. The intricacies of contemporary supply chains frequently present businesses with unexpected risks, which require managers to prioritize supply chain risk management in addition to economic benefits. Furthermore, environmental sustainability has become a central focus in SCM, reflecting a broader shift toward greener and more responsible business practices. This section explores some future perspectives on SCM.

4.1 Network and collaboration

With the development of industry and enrich logistics channels, the network structure has become a key characteristic of modern supply chains. Contemporary supply chains form large-scale networks of suppliers, manufacturers, distributors, retailers, and final consumers to enhance flexibility [27, 143]. Significant opportunities remain for industrial development and service improvement if SCN participants can achieve close cooperation, resource sharing, and information transparency; however, limited studies have examined large-scale SCNs, and the evolutionary and collaborative mechanisms of SCNs are not yet fully understood.

Although SCNs have significant potential to enhance overall effectiveness, cooperation between entities involved remains underdeveloped. The potential for improved performance is hindered by a lack of effective collaboration mechanisms that can facilitate seamless interaction between suppliers, manufacturers, distributors, and other stakeholders. Realizing the full benefits of an SCN requires more advanced optimization technologies and sophisticated management strategies to increase synergies between network participants. A new trend called horizontal collaborative logistics has emerged to enhance collaboration between organizations at the same supply chain level rather than between different tiers [144]. Moreover, the concepts of physical internet and intertwined networks have been proposed to create more efficient, sustainable, and flexible logistics operations [143, 145].

4.2 Resilience

Uncertainties are inherent at every stage of the supply chain and can propagate throughout the network, potentially leading to disruptions or even complete failure of supply chain services. Modern supply chains exhibit a trend of rapid change and networked topology, which can further amplify the impact of risks. Moreover, as the trend of economic globalization has been adversely affected by protectionist trade policies between countries, the risk of failure is rising. In particular, the COVID-19 pandemic triggered widespread failures across global supply chains [27] and supply chain risk management has become an increasingly critical area of focus in recent years.

Traditionally, SCM research has concentrated on supply chains' efficiency and costs; however, optimization can sometimes produce supply chains that are too fragile to bear risks. In such cases, supply chains' robustness and/or resilience must be considered [146]. A key aspect of risk management is to enhance network robustness amid uncertainties [23]. This approach is often addressed during the supply chain design phase. One study modeled the supply chain as a complex network and examined supply chain risk by analyzing the ripple effect of node failure to identify key nodes and enhance network flexibility [147]. Another study concentrated on networks' post-failure resilience, with an optimization goal of either the speed of recovery or its associated cost [90].

4.3 Green supply chain

In recent years, the effects of climate change have attracted growing attention to green supply chains [10]. Some similar concepts include environmental, sustainable, circular and closed-loop supply chains (CLSC) [148, 149]. In these cases, managers consider environmental impact in addition to economic considerations. Environmental considerations include carbon emissions, pollutants, and product recycling, among which reducing carbon emissions has been a focus of social and academic attention. Common approaches to incorporating environmental effects directly into SCM have been to quantify the weight of factors such as green products [150] and carbon emissions [151] as optimization variables for decision-making. In addition, carbon footprint tracking and carbon trading on the basis of the supply chain have also become operational matters, and carbon emissions management has matured using digital supply chain and digital-twin technology [69, 152].

In addition to incorporating environmental indicators into SCM, transforming the traditional supply chain is also an option. For example, the CLSC approach focuses on product recycling and reuse [149]. A key challenge in this area is designing reverse logistics networks [153], specifically selecting recycling points and developing recycling routes based on existing nodes to minimize new construction and reduce costs. Optimization in this context involves multiple considerations, including product production, recycling, logistics, and inventory management. Examining the circular flow of materials by integrating reverse logistics into traditional supply chains can help conserve resources and reduce carbon emissions.

4.4 Integration with advanced technologies

The proliferation of IT and automated technologies has profoundly reshaped SCM by introducing new capabilities that enhance efficiency, flexibility, and responsiveness. These technologies enable real-time tracking, data-driven decision-making, and seamless communication throughout the supply chain for more agile and resilient operations. For instance, technologies such as the IoT, which encompasses radio-frequency identification (RFID) [154] and blockchain [9] are being extensively integrated to improve automated management systems' efficiency. Moreover, intelligent equipment such as UAVs, intelligent robotic arms, and other new technologies is improving the efficiency of logistics and manufacturing [119, 120].

In particular, AI, which is closely intertwined with data-driven methodologies, is increasingly applied across various supply chain functions. By leveraging vast amounts of data and advanced algorithms, AI can enable companies to make more informed decisions, optimize operations, and enhance overall supply chain performance [2, 141, 155]. Our survey demonstrates the significant benefits of AI-based approaches in enabling systems to adapt to market dynamics, support automated management, and provide robust capabilities to solve inherently complex optimization problems in supply chain decision-making. In addition to its ability to optimize and forecast, AI can enhance customer service within the supply chain, particularly in areas such as customer support, order tracking, and issue resolution. For example, chatbots can interact with customers in real-time to answer questions, provide updates, and resolve problems. Indeed, generative AI models—particularly large language models (LLMs)—have emerged as a significant area of interest in both industry and academia. These models' ability to process and understand natural language, analyze unstructured data, and provide decision-support through automated insights makes them valuable tools for risk management, supplier communication, and knowledge transfer.

Nevertheless, it is essential to note that several challenges remain in using AI-based optimization and decision-making methods in SCM. While AI models rely on large, high-quality datasets to deliver accurate predictions and optimization results, many organizations' data may be fragmented, incomplete, or of poor quality, which can hinder the effectiveness of AI solutions [54]. Supply chains are subject to high uncertainty and variability from factors such as changing customer preferences, geopolitical risks, economic shifts, and weather disruptions. AI models may struggle to accommodate such variability, particularly when the historical data do not include unusual or unforeseen events. Moreover, supply chain data often contain sensitive information about suppliers, customers, and proprietary processes. Using AI to process and analyze these data can raise concerns related to data privacy and security, and privacy protection has become an important topic in SCM. Advanced technologies such as differential privacy and federated learning can enhance data security; however, their application in SCM requires further investigation [156]. Unreliability is another significant hindrance that impedes widespread AI adoption. For example, algorithmic bias in ML can result in unfair decisions, and hallucinations in LLMs can produce misleading recommendations. To unlock the potential for AI to inform the development of more reliable, efficient, and agile supply chains, more research is essential to address these issues to improve the reliability and effectiveness of AI applications.

5 Conclusion

This survey examines the application of optimization theory within the realm of SCM, covering four pivotal areas: inventory management, logistics, production planning, and demand forecasting, and providing an overview of the classical mathematical models and optimization algorithms used to make optimal decisions in this area. Considering the myriad challenges inherent in supply chains, we investigate the frameworks for addressing corresponding optimization problems. Additionally, the study encapsulates the recent trends of increased emphasis on risk management and environmental sustainability in contemporary SCM research. We also identify increased adoption of data-driven methodologies and AI technologies in SCM. While we do not claim to cover every facet of SCM, this survey can serve as a foundation and more exhaustive summaries are anticipated in the future as the field continues to evolve and expand.

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