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Logistics Systems in Industrial Engineering: An Operations Research Perspective

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Abstract. Modern logistics systems require coordinated decisions across production, inventory, warehousing, transportation, and supply networks. This narrative literature review examines these systems from an operations research (OR) perspective within industrial engineering. It summarizes the role of deterministic optimization, stochastic models, simulation, heuristics, and learning-assisted methods. It then reviews their applications in supply chain network design, inventory management, production scheduling, and warehouse optimization. The review shows that OR is most valuable when logistics is treated as an integrated system rather than a set of isolated activities. Traditional models remain essential for structured and stable problems, while uncertain and dynamic environments increasingly require adaptive, data-supported approaches. Future progress will depend on real-time model updating, multi-objective decision-making, and digital twins, as well as the integration of intelligent methods with explicit OR constraints and system-level objectives.

Keywords: Industrial engineering, Logistics systems, Operations research, Decision-making

1. Introduction

Logistics systems are central to industrial engineering because they coordinate the movement of materials, information, and resources across production, warehousing, transportation, and markets. E-commerce, intelligent manufacturing, and global supply networks have increased interdependence, uncertainty, and the required speed of decision-making. Operations research (OR) supports these decisions by representing logistics relationships through quantitative models and evaluating trade-offs among cost, time, capacity, and service.

Deterministic models remain important when system parameters are sufficiently stable, but modern logistics increasingly requires adaptive decision methods. Dynamic job arrivals, equipment changes, and limited transport resources can make a fixed schedule obsolete; therefore, Li et al. applied multi-agent deep reinforcement learning to real-time production-logistics scheduling [1]. At the supply-chain level, disruptions may spread across multiple echelons, and Liu et al. combined causal Bayesian networks with mathematical programming to reduce such risks under limited intervention budgets [2]. These studies illustrate a broader shift from one-time optimization toward adaptive and resilient decision support.

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This paper presents a narrative literature review and considers both foundational OR studies and recent logistics applications. Supply chain network design, inventory management, production scheduling, and warehouse optimization are selected because they represent strategic, tactical, and operational decisions. The central argument is that OR creates the greatest value when these decisions are coordinated at the system level rather than optimized independently. The review therefore examines major methods, application patterns, current challenges, and future directions in data-driven and sustainable logistics.

2. Theoretical background

2.1. Operations research methods in logistics systems

OR provides a quantitative foundation for logistics decision-making by converting operational problems into decision variables, objectives, and constraints. Questions such as how much to ship, where to allocate capacity, and how to sequence tasks can then be evaluated systematically rather than through intuition alone [3]. The appropriate method depends on the problem's structure, scale, uncertainty, and time constraints.

When demand, cost, travel time, and capacity are treated as known, deterministic models are generally appropriate. Linear and mixed-integer programming support transportation allocation, facility location, vehicle assignment, and scheduling, whereas network models capture material flows among suppliers, plants, warehouses, and customers. The vehicle routing problem is a classic example in which routes are selected under capacity and service constraints [4].

When demand, lead times, capacity, or supply availability are uncertain, the model must account for multiple possible outcomes. Stochastic programming evaluates decisions across scenarios instead of relying on a single parameter set [5]. Risk-oriented models can further combine probabilistic relationships with optimization to improve supply chain resilience [2].

For large-scale or rapidly changing systems, exact offline optimization may be too slow to support execution. Heuristics, simulation, rolling optimization, and learning-assisted methods are therefore used to generate high-quality decisions within limited response time. Multi-agent reinforcement learning, for example, has shown potential for real-time task scheduling and automated guided vehicle dispatching [1]. OR should consequently be viewed as a flexible toolkit whose methods are suited to deterministic, uncertain, large-scale, or dynamic logistics conditions.

2.2. Industrial engineering and logistics systems

Industrial engineering (IE) focuses on the design and improvement of integrated systems involving people, equipment, materials, information, energy, and processes. Its distinguishing feature is system-level optimization: improving overall performance rather than optimizing a single activity in isolation [6]. Logistics is therefore a natural IE field because its outcomes depend on interactions among functions and resources.

From an IE perspective, logistics includes procurement, inbound supply, production logistics, inventory control, warehousing, material handling, transportation, distribution, and reverse logistics. These activities are interdependent. Inventory policies affect warehouse space and capital use; production schedules influence delivery timing; warehouse layout affects picking performance; and transportation decisions shape service. A local improvement may therefore transfer cost or congestion to another part of the system.

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IE seeks to reduce non-value-added handling, waiting, excess inventory, repeated operations, and information delays [7]. It also considers the relationships among throughput, cycle time, work-in-process, capacity, and variability. Excess work-in-process can increase congestion and waiting, while insufficient capacity creates persistent bottlenecks [8]. Effective logistics improvement must therefore balance cost, time, service, resource utilization, and flow stability. OR complements this systems perspective by quantifying trade-offs and coordinating decisions across logistics processes.

2.3. Operations research and logistics decision-making

Logistics decisions differ in time horizon, investment level, reversibility, and operational impact. They are commonly classified as strategic, tactical, and operational decisions [9, 10], and OR supports each level differently.

Strategic decisions define the long-term structure of the logistics system. They include facility location, network configuration, supplier selection, and capacity expansion. Because these decisions require substantial investment and are difficult to reverse, mixed-integer and network models are used to compare alternative configurations under capacity, flow, cost, and service constraints [3].

Tactical decisions convert the strategic structure into medium-term resource plans, including inventory policies, transportation capacity, production plans, workforce levels, and warehouse capacity allocation. Inventory models, stochastic programming, and simulation help determine operating parameters while balancing cost, service, resource utilization, and uncertainty [5, 9].

Operational decisions concern daily or real-time execution, including routing, order picking, automated guided vehicle dispatching, job sequencing, and rescheduling. Because system structure is largely fixed at this level, the emphasis is on fast resource allocation and timely response. Heuristics, rolling optimization, simulation, and learning-based methods are useful when exact solutions cannot be obtained within the time available for decisions [1].

3. Applications of operations research in logistics systems

3.1. Supply chain network design

Supply chain network design determines the long-term configuration of plants, warehouses, distribution centers, customer markets, and the flows connecting them. Facility number, location, and capacity influence transportation distance, delivery time, fixed cost, and service performance. The problem is therefore systemic: changing one node may affect the cost and responsiveness of the entire system.

OR represents network design through linear, mixed-integer, and multi-objective models. Altiparmak et al. considered total cost, customer service, and the balance of capacity utilization simultaneously [11], showing that network design rarely pursues a single objective.

Economic efficiency must also be balanced against uncertainty and resilience. Baghalian et al. developed a stochastic network design model that integrates facility location, inventory, and shipment decisions under supply and demand uncertainty [12]. This approach recognizes that a low-cost network may perform poorly when facilities fail or demand departs from the original plan.

Environmental requirements further broaden the decision criteria. Elhedhli and Merrick incorporated CO_2 emission costs into warehouse-location and product-flow decisions [13]. Together, these studies show an evolution from cost-based network design toward multi-objective models that jointly consider service, uncertainty, resilience, and environmental impact. OR therefore provides a

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structured basis for comparing strategic configurations whose advantages cannot be judged by cost metrics alone.

3.2. Inventory management

Inventory management balances the cost of holding stock against the operational and service consequences of shortages. Excess inventory occupies space and capital, while insufficient inventory can interrupt production, delay orders, and reduce service levels. OR translates this trade-off into replenishment policies that connect ordering decisions with demand, lead time, shortage risk, and service requirements.

Classical models provide the basic logic. The economic order quantity model balances ordering and holding costs, while continuous-review (r, Q) policies specify when and how much to replenish. Federgruen and Zheng developed an efficient method for computing optimal parameters for such systems [14].

Fixed parameters become less reliable when demand, lead times, or supply availability vary. Stochastic programming evaluates replenishment decisions across possible scenarios [5], so the optimal inventory level is treated as a policy shaped by risk and service requirements rather than a fixed quantity. This perspective is particularly important when average demand conceals peaks, delays, or product-specific variation.

Deng et al. demonstrated this transition in Alibaba's retail operations by integrating simulation optimization, demand forecasting, inventory management, pricing, and recommendation tools [15]. The case shows how classical inventory principles can be extended for large-scale, multi-product systems. The broader development is from fixed replenishment rules toward adaptive control where forecasts, operational data, and optimization are updated jointly.

3.3. Production scheduling and warehouse optimization

Production scheduling assigns jobs to limited machines and determines processing order and timing. The objective is not simply to maximize individual machine utilization, because excessive local loading may increase work-in-process, waiting, and total flow time [8]. Scheduling must coordinate jobs, machines, transport resources, and due dates at the system level.

Scheduling also involves multiple objectives. Dai et al. incorporated transportation time into a flexible job shop model and minimized both makespan and energy consumption [16]. Their study illustrates why production and internal logistics should not be optimized separately: a schedule that ignores material movement may be infeasible or inefficient.

Shop-floor conditions are rarely static. New orders, priority changes, equipment states, and limited automated guided vehicle capacity can quickly invalidate a fixed plan. Li et al. addressed dynamic job arrivals and transport constraints through multi-agent deep reinforcement learning [1]. This reflects a shift from generating a fixed schedule before production toward adapting decisions in response to system state changes.

Warehouses face a comparable coordination problem involving orders, storage locations, robots, racks, and workstations. In JD.com's intelligent warehouse system, Qin et al. used large-scale integer programming to support real-time dispatching among these resources [17]. The case indicates that automation creates value only when assignment, routing, and dispatching decisions are coordinated. Across both production and warehousing, OR is moving from static sequencing toward integrated and executable control within capacity and time constraints.

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4. Discussion

4.1. Challenges

A major challenge is maintaining decision quality while logistics conditions change continuously. Orders, equipment states, transport capacity, and resource availability may change before an offline solution is applied. Although IoT devices and digital platforms provide more timely information, model updating, data quality, compatibility, and computation time still determine whether a recommendation is actionable. Ivanov and Dolgui describe a digital supply chain twin based on real-time network states, emphasizing the need to connect observation, modeling, optimization, execution, and feedback [18].

A second challenge is balancing economic performance with resilience and sustainability. Emissions need to be incorporated into facility, routing, and allocation decisions rather than assessed only after operations [13]. Meanwhile, demand variation, supply interruption, and facility failure may propagate across multi-echelon networks [2]. These objectives often conflict: faster delivery may require additional transport, while safety stock and spare capacity improve resilience but increase cost and resource use. Practical logistics optimization must generate feasible decisions quickly while balancing cost, service, environmental impact, and risk rather than maximizing a single indicator.

4.2. Future directions

Future research is likely to emphasize hybrid decision frameworks. Machine learning can identify patterns and support computationally expensive decisions, whereas OR enforces explicit constraints, feasibility, and system-level objectives [19]. This combination is especially relevant to large-scale scheduling, routing, and warehouse systems that require frequent updates and cannot rely entirely on fixed assumptions.

Digital twins provide a practical environment for this integration. Real-time data update system states, simulation evaluates alternatives, and optimization generates executable actions before implementation [18]. Future models should treat uncertainty, emissions, disruption risk, and resource load as formal and adjustable objectives. Research should also address data governance, computational scalability, and the interpretability of recommendations for operational users. The likely direction is a shift from one-time optimization toward continuous decision support that coordinates strategic, tactical, and operational levels while balancing efficiency, resilience, and sustainability.

5. Conclusion

This study examines logistics systems in industrial engineering from an OR perspective. The evidence shows that OR provides a structured way to represent logistics decisions and supports long-term design, medium-term planning, and real-time execution. Applications in network design, inventory management, production scheduling, and warehouse optimization consistently indicate that logistics performance depends on coordination across resources and processes rather than isolated local improvements.

The review synthesizes these applications from the system-level perspective of industrial engineering. Deterministic optimization remains an essential foundation, while stochastic, simulation-based, heuristic, and learning-assisted methods are increasingly important under

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uncertainty and rapid change. In practice, their value lies in helping organizations balance cost, service, resource utilization, resilience, and environmental performance.

The study is limited by its narrative and selective review design. It does not provide empirical testing, a systematic search protocol, or a quantitative comparison of algorithms. Future work could conduct systematic reviews and data-based comparisons, with particular attention to dynamic multi-objective optimization, digital twins, and the integration of OR with data science.

Overall, OR remains central to logistics system design and management. Its future role will depend on combining rigorous models with timely data and adaptive decision mechanisms while retaining feasibility, transparency, and a system-level view of logistics performance.

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