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Integrated Production and Outbound Distribution Scheduling: a hybrid framework

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ABSTRACT

The integrated production and outbound distribution scheduling (IPODS) framework presented in this paper addresses the critical need for coordinated manufacturing and distribution in industrial engineering and supply chain management. The proposed solution employs the Ant Colony System (ACS) to optimize production scheduling and vehicle routing. The framework comprises four stages: production scheduling, order completion and patch formation, vehicle assignment, and vehicle routing with departure time optimization. Initially, ACS is utilized to determine optimal schedules for parallel machine production, minimizing overall production time. Subsequently, order completion times are calculated, and orders are grouped into patches to streamline logistics. These patches are then assigned to vehicles from an available fleet, ensuring efficient utilization and load balancing. Finally, ACS is applied to solve the vehicle routing problem, determining optimal routes and departure times to minimize travel costs and ensure timely deliveries. This framework enhances the efficiency and effectiveness of managing integrated production and distribution tasks, providing significant and improved operational performance.

1. Introduction

Integrated production and outbound distribution scheduling (IPODS) is essential in the fields of industrial engineering and supply chain management. This concept involves coordinating manufacturing processes with the subsequent distribution of finished products. The primary goal is to boost both production efficiency and delivery performance [1]. By aligning production schedules with distribution plans, companies aim to cut costs, reduce lead times, and improve overall operational efficiency [2].

In the past, production and distribution activities were often managed separately, which led to increased costs and suboptimal performance [3]. This separation can cause bottlenecks, excessive inventory, and delays in meeting customer demands [4]. However, integrated scheduling tackles these challenges by harmonizing production and distribution activities. This ensures that production output matches distribution capabilities, leading to a smoother and more efficient supply chain operation [5].

A critical aspect of IPODS is developing mathematical models and algorithms to effectively coordinate production and distribution schedules. These models typically consider various factors such as production capacities, transportation constraints, inventory levels, and customer demand patterns [6]. By incorporating these elements, the models can generate schedules that optimize resource use, minimize costs, and ensure timely delivery of products. Balancing the trade-offs between production efficiency and distribution effectiveness is a key

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challenge in IPODS. For example, producing large batches of products may be cost-effective from a manufacturing perspective, but it can lead to higher inventory holding costs and distribution delays. Conversely, producing smaller batches can reduce inventory costs and improve responsiveness to customer demands, but may result in higher production costs due to frequent setup changes. Integrated scheduling models strive to find an optimal balance that maximizes overall supply chain performance [7].

Recent advancements in information technology and data analytics have significantly contributed to the development of more sophisticated IPODS models. The use of real-time data, advanced forecasting techniques, and machine learning algorithms allows for more accurate demand predictions and more responsive production and distribution schedules. Additionally, integrating IPODS with enterprise resource planning (ERP) systems and supply chain management software provides a seamless flow of information across the entire supply chain, enhancing coordination and decision-making [8].

Implementing IPODS offers numerous benefits. Companies can achieve substantial cost savings through improved resource utilization, reduced inventory levels, and lower transportation costs. Moreover, better coordination between production and distribution activities leads to improved customer service levels, as products are delivered more reliably and on time. This, in turn, can increase customer satisfaction and loyalty [9-11].

In conclusion, integrated production and outbound distribution scheduling is a crucial strategy for modern supply chain management. By aligning production processes with distribution activities, companies can achieve greater efficiency, cost savings, and customer satisfaction. As the business environment becomes increasingly competitive and complex, the importance of effective IPODS will continue to grow, driving further innovations and advancements in this vital area of industrial engineering and supply chain management.

The remaining sections of the research are organized as follows: In Section 2, the Literature Review, an overview of existing research and theoretical foundations, identifying gaps and contextualizing the current study. Section 3, the Problem Statement, clearly defines the research problem, outlining the specific issues or challenges that the study aims to address. Section 4, Methodology, details the research design, methods, and procedures employed. Section 5, The Proposed Framework, introduces the proposed framework, explaining its components and how it addresses the identified problem. Finally, Section 6, the Conclusion, summarizes the key findings, discusses their implications, and suggests potential directions for future research.

2. Literature review

The optimization of production planning, distribution, and scheduling is a cornerstone of industrial engineering, critical for enhancing efficiency and meeting the ever-increasing demands of customers. Over the years, extensive research has been conducted to address these complex issues. Prior comprehensive reviews have laid a strong foundation in this field, with [12] covering the advancements up to 2016 and [13] extending the review from 2017 to early 2022. Building on these foundational reviews, our current review focuses on the most recent developments from 2022 to the present. This period has witnessed significant innovations in Integrated Production, Distribution, and Scheduling Problems (IPDSP). Recent studies have explored a variety of advanced methodologies, including mixed-integer linear programming models, hybrid algorithms, and multi-objective evolutionary algorithms. These approaches aim to improve production efficiency, minimize costs, and optimize scheduling in dynamic and uncertain environments.

In this review, we synthesize the findings from the latest research, providing a detailed examination of the methodologies and their practical applications in integrated production and distribution systems. Our aim is to offer insights into the most current trends and advancements, building on the substantial body of knowledge established by the preceding reviews.

Tibaldo, et al. [14] discuss the concept of lot sizing within the context of production planning, particularly in Integrated Production, Distribution, and Scheduling Problems (IPDSP). Lot sizing, which involves dividing customer orders or demands into batches for processing in different units, is crucial when dealing with perishability as it allows for parallel production and expedited shipping. Incorporating lot sizing into production planning models can improve delivery times, enhance production capacity utilization, and optimize resource efficiency. The terms "lot sizing" and "batching problem" are used interchangeably, referring to decisions on batch sizes for product orders. The document also highlights a mixed-integer linear programming model that integrates batching, production, and distribution activities across multiple batch production plants with non-identical units to optimize the allocation of customer demands.

Atasagun and Karaoğlan [15] explore the Integrated Production, Order Acceptance, and Distribution Scheduling problem with Multiple Plants and Multiple Vehicles, focusing on perishable products. Their goal is to optimize production, order acceptance, and distribution scheduling to maximize efficiency while considering various constraints and objectives. They propose a mixed-integer programming (MIP) formulation for small instances and a Variable Neighborhood Search (VNS) algorithm for larger instances. Similarly, Horváth [16] addresses the integrated production and outbound distribution scheduling problem, aiming to optimize supply chain operations by minimizing the makespan, defined as the return time of the vehicle after completing its final trip. They propose a variable neighborhood search approach incorporating two new local search operators to tackle this challenge effectively.

Su, et al. [17] and Zhang, et al. [18] both focus on minimizing the maximum completion time in their respective studies. Su, et al. [17] present an ensemble method called EGTOA-SA, which combines group teaching optimization and simulated annealing. This approach proves to be superior through comparisons with other optimization algorithms and a mathematical programming solver, showcasing its effectiveness in addressing the scheduling issue. On the other hand, Zhang, et al. [18]discuss the integration of production and distribution in supply chains, focusing on scheduling flexible job shops and distribution to minimize the maximum completion time. They propose a cooperative evolutionary algorithm with simulated annealing that utilizes three populations to search for factory assignment, machine assignment, and operation sequence. The cooperation strategy and heuristic rule implemented in their model demonstrate its competitiveness and efficiency in solving the integration problem.

Guo, et al. [19] and Tan, et al. [20] address the complexities of integrating production and distribution scheduling in dynamic and uncertain environments. Guo, et al. [19] tackle the Integrated Distributed Production and Distribution Scheduling Problem in Group Manufacturing, considering Uncertain Travel Time (IDPDSP-GM-UTT). They propose a joint distributed hybrid flow-shop production and batch distribution scheduling approach that accounts for uncertain travel times, aiming to minimize the total cost involved in the production and distribution process. Tan, et al. [20] focus on the integrated scheduling of distributed production and distribution (ISDPD) in the manufacturing industry, emphasizing the need for shared transportation resources (STR) and a flexible job shop production environment within the ISDPD framework. They highlight the computational challenges associated with solving ISDPD problems efficiently and propose various initialization methods, such as scoring-based, saving-based, batch-based, and earliest-departure rule initialization methods, to optimize production efficiency and scheduling.

Hou, et al. [21] and Luo, et al. [22] both address multi-objective optimization in their respective research. Hou, et al. [21] discuss the integrated green production and distribution scheduling, where decisions need to be made regarding factory assignment, job processing sequences, processing speeds, vehicle allocation, and delivery sequences. Their objective is to minimize two main criteria: total tardiness (TT) and total carbon emissions (TCE). They propose a Q-learning-based multi-objective evolutionary algorithm (Q-MEA) to balance time efficiency, energy consumption, and carbon emissions in a distributed flow shop setting. Luo, et al. [22] focus on a bi-objective integrated scheduling problem (PISP) involving production, inventory, and distribution activities simultaneously to minimize total earliness/tardiness (E/T) penalty costs and total energy consumption. They employ a modified NSGA-II (MNSGA) as a solving technique, introducing a three-layer encoding method for chromosome representation, adaptive crossover, and mutation operators for global search, and an objective-oriented local search operator to enhance local exploitation ability.

Fu, et al. [23] and Zhang, et al. [24] propose hybrid algorithms to solve integrated scheduling problems. Fu, et al. [23] address the integrated scheduling of an open shop production phase and a vehicle routing distribution phase. They formulate the problem as a mixed integer programming model to optimize job allocation among groups, group processing routes and sequences on machines, job assignment among vehicles, and delivery routes of vehicles, aiming to minimize the maximum completion time (MCT). They propose a hybridization algorithm combining Brainstorm Optimization (BSO) and Q-learning, demonstrating its effectiveness and competitiveness through comparisons with existing meta-heuristics and an exact solver CPLEX. Similarly, Zhang, et al. [24] focus on an Integrated Production and Distribution Scheduling (IPDS) problem with the objective of minimizing makespan and total weighted earliness and tardiness in a two-stage process involving production and distribution. They combine Brainstorm Optimization (BSO) with a Reinforcement Learning (RL) algorithm, specifically Q-learning, to address the IPDS problem, showcasing its superiority over existing meta-heuristics and optimization tools in generating high-quality solutions.

Based on the comprehensive review of recent advancements in Integrated Production, Distribution, and Scheduling Problems (IPDSP) from 2022 to the present, future research should focus on several key areas. One crucial direction is the development of more sophisticated algorithms, incorporating emerging techniques such as deep learning and neural networks to handle increasing complexity and scale. Additionally, real-time and adaptive scheduling solutions are needed to respond promptly to dynamic production and distribution conditions, including uncertainties and disruptions. Sustainability and green logistics should also be prioritized, with models that balance economic performance and environmental impact, emphasizing carbon emissions, energy consumption, and waste reduction. The integration of IoT and Industry 4.0 technologies presents opportunities for smarter decision-making processes through real-time data and predictive maintenance. Moreover, the trend towards mass customization necessitates flexible production systems that can adapt to varying customer demands. Collaborative and distributed manufacturing networks require new optimization models for efficient coordination. Future research should also explore multi-criteria decision-making approaches to balance conflicting objectives like cost, time, quality, and sustainability. Empirical studies and real-world applications are essential to validate theoretical advancements, with case studies from different industries demonstrating practical applicability. Integrating human expertise with automated systems can enhance overall efficiency, highlighting the importance of human-machine collaboration. Finally, understanding the impact of policies and regulations on IPDSP is crucial, as companies must adapt their strategies to different regulatory environments effectively. Addressing these areas will push the boundaries of integrated production, distribution, and scheduling, leading to more efficient, sustainable, and resilient industrial systems.

Based on the provided gaps, we will examine the ant colony system to solve the proposed problem with more realistic dimensions such as parallel machine scheduling in production stage while using a fleet of vehicles in distribution stage which dealt as a vehicle routing problem. We also examine dividing the orders into batches and determine the optimal time for each vehicle to start its trip.

3. Problem statement

This study addresses the challenges within a time-sensitive make-to-order (MTO) supply chain that encompasses both production and distribution stages. As shown in Figure 1, in the production phase, the plant (serving as either the producer or supplier) utilizes identical machines to process individual customer items concurrently, with each item representing a specific customer order. Once the items are completed, they enter the distribution phase, where they are transported to their respective customer destinations by vehicles, adhering to predetermined customer time windows.

All vehicles initiate their journeys from the plant depot and return to the same location after completing their deliveries. For each customer item, delivering earlier than the lower limit of its time window results in an earliness penalty, while delivering later than the upper limit incurs a tardiness penalty.

The core problem lies in determining the optimal allocation of customer items to machines and vehicles, sequencing the item processing on the machines, and planning the delivery routes and departure times of the vehicles. The primary objective is to minimize the total distribution cost, which includes both transportation costs and the penalties associated with time window violations.

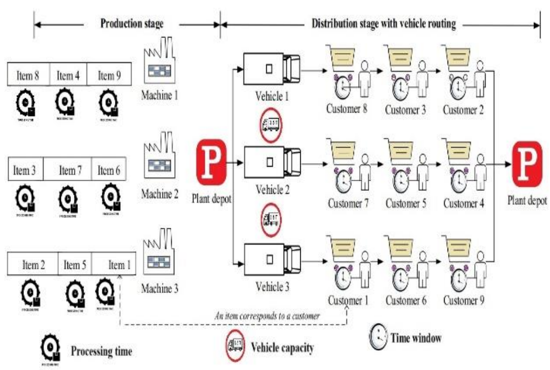

Fig. 1. An example of integrated production and distribution problem.

4. Methodology

The Ant Colony System (ACS) is a heuristic optimization approach inspired by the natural foraging behavior of ants. It mimics how ants discover efficient routes to food by leaving and following pheromone trails, which guide subsequent ants in their path selection. This algorithm is particularly effective for solving intricate combinatorial optimization problems, such as the Traveling Salesman Problem (TSP), where the objective is to determine the shortest possible route that visits each city exactly once and returns to the starting point. Figure 2 shows the flowchart of main steps of ACS.

In ACS, the process begins with ants constructing solutions by traversing a network of nodes. Their movement is influenced by two primary factors: pheromone intensity and heuristic information. Pheromones, which are chemical markers left on paths by ants, affect the probability of other ants choosing those same paths. As ants travel, they deposit pheromones proportional to the quality of their solutions—shorter routes receive more pheromone deposits. The pheromone level on an edge connecting nodes i and j at time t is updated using:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(t) \qquad (1)$$

The quantity of pheromone deposited on an edge is determined by the quality of the solution found. For each ant, the pheromone increments $\Delta\tau_{ij}$ on edge (i,j) is calculated as:

$$\Delta\tau_{ij}^{k} = \frac{Q}{L_k} \qquad (2)$$

where L_k represents the tour length created by ant k, and Q is a scaling constant. Ants that discover shorter tours contribute more pheromone, thus reinforcing these paths.

Ants choose their next step based on a probability function that integrates both pheromone levels and heuristic information. The probability p_{ij} of selecting edge (i,j) when at node i is computed using:

$$p_{ij}^{t} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\Sigma_{l \in allowed}[\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta}} \qquad (3)$$

In this formula, η_{ij} denotes heuristic information, such as the reciprocal of the distance between nodes i and j. The parameters α and β control the impact of pheromone intensity and heuristic data, respectively.

The algorithm starts with an initial pheromone level across all edges. Ants then iteratively build solutions, and after each iteration, pheromone levels are updated according to the solutions found, with better solutions receiving more pheromone. This iterative process continues until a stopping condition is met, such as a set number of iterations or convergence to a stable solution.

By combining global search capabilities provided by pheromone trails with local search advantages from heuristic information, ACS proves to be a versatile and effective method for addressing a variety of complex optimization problems.

4.1. Algorithm Steps

1. Initialization: Initialize pheromone levels τ_{ij} on all edges.
2. Ants Construction: Deploy ants to construct solutions based on the probability function.
3. Pheromone Update: Update pheromone levels on the edges based on the solutions found.
4. Repeat: Repeat the process for a predefined number of iterations or until convergence.

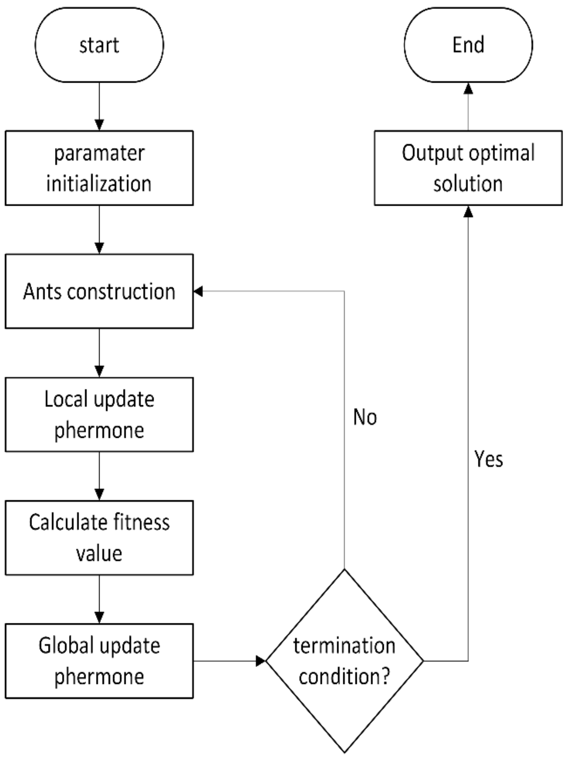

Fig. 2. Flowchart of Ant colony system.

5. The proposed hybrid framework

The proposed framework addresses the integrated parallel machine production and vehicle routing problem by employing an Ant Colony System (ACS) to optimize production scheduling and vehicle routing. The framework consists of several stages, each leveraging ACS for enhanced efficiency. This comprehensive approach ensures that production and distribution processes are aligned and efficient, minimizing delays and costs.

5.1. Production Scheduling Using Ant Colony System

5.1.1. Overview

The initial stage of the framework involves the use of ACS to tackle the production scheduling problem. Here, the ACS algorithm is utilized to determine the optimal schedule for production tasks across parallel machines. The objective is to minimize the overall production time and ensure the timely completion of each order. The ACS algorithm simulates the behaviour of ants finding paths to optimize the scheduling of production tasks. By adjusting pheromone levels and exploring various scheduling configurations, the algorithm identifies the most efficient schedule that aligns with production constraints.

5.1.2. Detailed Process:

- *Task Identification:*

All production tasks are identified, including their respective processing times and machine requirements.

- *ACS Initialization:*

The ACS algorithm is initialized, setting initial pheromone levels uniformly. Each ant in the system represents a potential solution to the scheduling problem.

- *Ant Movement and Solution Construction:*

Ants traverse through the task nodes, constructing potential schedules. They probabilistically select the next task based on pheromone levels and heuristic information (e.g., shortest processing time).

- *Pheromone Update:*

After all ants have constructed their schedules, pheromone levels are updated. Successful paths (schedules that minimize production time) receive increased pheromone levels, guiding future ant movements.

- *Iteration and Convergence:*

The process iterates, with ants continuously updating their solutions and pheromone levels until convergence is achieved. The optimal schedule is the one with the highest pheromone level and the least total production time.

- *Output:*

The final output is the optimal schedule for all production tasks, ensuring that each machine's utilization is maximized, and overall production time is minimized.

5.2. Order Completion Time and Patch Formation

5.2.1. Overview

Once the production schedule is determined, the next step involves calculating the completion time for each order. These completion times are crucial for managing the subsequent logistics. Orders are then divided into patches based on their completion times. This division ensures that orders are grouped in a way that optimizes the logistics and transportation process. Each patch represents a set of orders that are scheduled for delivery together, which simplifies the routing and assignment processes in the next stages.

5.2.2. Detailed Process:

- *Completion Time Calculation:*

Based on the production schedule, the completion time for each order is calculated. This includes accounting for any dependencies between tasks and the sequence in which they are processed.

- *Order Grouping:*

Orders are grouped into patches based on their completion times. This step involves clustering orders that are completed within a similar time frame.

- *Patch Formation:*

Each patch represents a batch of orders that are scheduled for delivery together. The grouping aims to simplify the logistics process and enhance the efficiency of vehicle routing.

- *Optimization of Patches:*

The patches are optimized to balance the load across different delivery time frames, ensuring that no single patch is overloaded.

5.3. Vehicle Assignment

5.3.1. Overview

With the patches established, the framework proceeds to allocate each patch to a vehicle from the available fleet. This step involves assigning patches to vehicles in a manner that optimizes fleet utilization and balances the load across vehicles. The allocation is based on factors such as vehicle capacity, availability, and operational constraints. The goal is to ensure that each vehicle is assigned a patch that it can efficiently handle, considering both the physical capacity and the scheduling requirements.

5.3.2. Detailed Process:

- *Vehicle* Fleet Assessment:

The current fleet of vehicles is assessed, including their capacities, availability, and operational constraints (e.g., maximum driving hours, maintenance schedules).

- *Patch Allocation:*

Each patch is allocated to a vehicle in a way that optimizes fleet utilization. The assignment considers factors such as vehicle capacity, geographical location, and delivery deadlines.

- *Balancing Load:*

The allocation process aims to balance the load across the fleet. Overloading a single vehicle is avoided to ensure that all vehicles operate efficiently.

- *Constraint Handling:*

Operational constraints, such as maximum load capacity and route restrictions, are strictly adhered to during the allocation process.

5.4. Vehicle Routing and Departure Time Optimization

5.4.1. Overview

The final stage involves using the ACS to determine the optimal routes for each vehicle assigned to a patch. The vehicle routing problem (VRP) is addressed by applying the ACS to find the most efficient paths that minimize travel time and cost. Additionally, the optimal departure time for each vehicle is determined using a predefined procedure. This procedure integrates the production completion times and routing constraints to ensure that vehicles depart at times that align with their assigned routes and avoid delays.

5.4.2. Detailed Process:

- *Route Initialization:*

Initial routes are generated for each vehicle based on the geographical locations of the orders in each patch.

- *ACS for Route Optimization:*

The ACS algorithm is applied to optimize these routes. Ants explore different paths, updating pheromone levels based on the efficiency of each route.

- *Cost Minimization:*

The algorithm aims to minimize travel time and cost, considering factors such as distance, traffic conditions, and delivery priorities.

- *Departure Time Calculation:*

Optimal departure times for each vehicle are determined. This step integrates production completion times with route constraints to ensure timely deliveries.

- *Iteration and Adjustment:*

The routing and departure time optimization process iterates until the most efficient routes and schedules are found.

- *Final Output:*

The final output includes the optimal routes for each vehicle and their respective departure times, ensuring that deliveries are completed within the required time frames.

In summary, as shown in Figure 3, this framework effectively integrates the ACS for both production scheduling and vehicle routing. By sequentially addressing production scheduling, order patching, vehicle assignment, and route optimization, the framework aims to enhance the overall efficiency and effectiveness of managing parallel machine production and vehicle routing tasks. This detailed explanation covers each step in the proposed hybrid framework, providing a comprehensive understanding of how ACS is employed to optimize both production scheduling and vehicle routing.

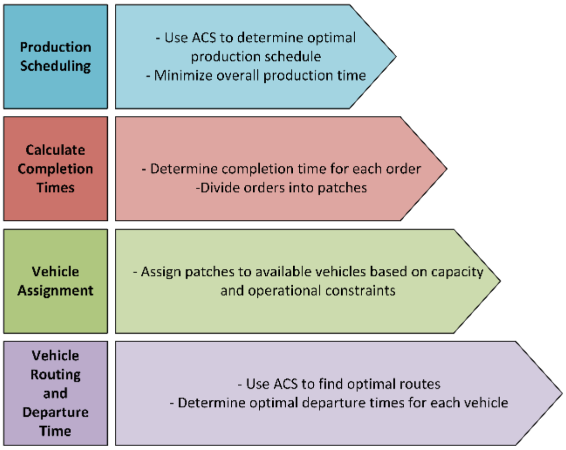

Fig. 3. The proposed framework for solving the IPODS problem.

6. Conclusion

The study presents a comprehensive framework for solving the integrated parallel machine production and vehicle routing problem, leveraging the capabilities of the Ant Colony System (ACS). By addressing production scheduling, order patching, vehicle assignment, and route optimization sequentially, the proposed solution effectively enhances the coordination between production and distribution activities. The use of ACS in both production scheduling and vehicle routing ensures optimal resource utilization and cost minimization. The integration of completion times, patch formation, and optimal departure times further refines the logistics process, leading to significant improvements in overall supply chain performance. As the competitive and complex business environment evolves, the importance of such integrated scheduling frameworks will continue to grow, driving further innovations and advancements in industrial engineering and supply chain management. Future research should focus on incorporating real-time data, advanced forecasting techniques, and sustainability considerations to further enhance the robustness and applicability of the proposed framework.

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