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Reshaping Coordination Efficiency in the Textile Supply Chain Through Intelligent Scheduling Technologies

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Abstract: The textile industry, characterized by its complex and globally dispersed supply chains, faces significant challenges in coordination efficiency due to fragmented information flows and dynamic production demands. Traditional scheduling methods struggle to meet the increasing requirements for customization, rapid delivery, and sustainability. This paper explores the transformative potential of intelligent scheduling technologies—leveraging advances in artificial intelligence, IoT, and big data analytics—to reshape coordination efficiency across the textile supply chain. Through the integration of dynamic resource allocation and real-time production optimization, intelligent scheduling addresses critical issues such as short product life cycles and high-mix low-volume manufacturing. The study provides a comprehensive review of current technological approaches and sets the stage for subsequent case studies and simulation analyses demonstrating tangible operational improvements.

Keywords: textile supply chain; intelligent scheduling; coordination efficiency; artificial intelligence

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1. Introduction

1.1. Background: Complexity and Digitalization in the Textile Supply Chain

The textile industry represents one of the most globally integrated and structurally complex manufacturing sectors. A typical textile supply chain encompasses multiple interconnected stages, including raw material procurement, spinning, weaving, dyeing, garment manufacturing, logistics, and retail [1]. These stages often span across different geographic regions and involve numerous stakeholders, leading to fragmented information flows, inconsistent production schedules, and inefficiencies in coordination.

In recent years, the global push toward digital transformation has significantly impacted the textile industry [2]. With increasing consumer demands for customization, faster delivery, and sustainability, traditional scheduling approaches based on manual planning or rigid rules can no longer satisfy the dynamic needs of modern production systems. As a result, textile enterprises are compelled to rethink their coordination mechanisms across the supply chain, seeking more responsive, data-driven, and intelligent solutions [3].

1.2. Rise of Intelligent Scheduling Technologies

Intelligent scheduling technologies—driven by advancements in artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and edge computing—are emerging as a key enabler of smart manufacturing [4]. These technologies aim to dynamically allocate resources, optimize production sequences, and respond in real-time to changes in order specifications, machine availability, or supply disruptions.

In the context of the textile industry, intelligent scheduling plays a critical role in addressing core challenges such as short product life cycles, high-mix low-volume orders, and the need for synchronized operations across dispersed production units [5]. Technologies such as Advanced Planning and Scheduling (APS) systems, genetic algorithms, deep reinforcement learning, and cyber-physical systems (CPS) have shown potential to enhance flexibility, reduce lead times, and increase utilization rates within complex supply networks.

1.3. Research Objectives and Structure of the Paper

This study aims to explore how intelligent scheduling technologies can reshape coordination efficiency across the textile supply chain. Specifically, the paper addresses the following research questions:

What are the main coordination challenges in textile supply chains that intelligent scheduling can help solve?

Which intelligent scheduling methods are most suitable for textile-specific production constraints?

How can digital scheduling tools be integrated into existing textile manufacturing systems to enable multi-site coordination?

What empirical evidence or simulation results support the effectiveness of intelligent scheduling in improving supply chain performance?

2. Background and Literature Review

2.1. Coordination and Scheduling in Supply Chains

Effective coordination and scheduling have long been recognized as central issues in supply chain management (SCM) [6]. Coordination refers to the alignment of decision-making and operations among multiple entities to achieve global optimization, while scheduling focuses on the allocation of tasks, resources, and time slots within and across manufacturing facilities.

Traditional scheduling approaches, such as rule-based heuristics or fixed priority dispatching, often fail to meet the real-time and multi-objective demands of modern supply chains. This is especially true in industries with high product variability and short delivery cycles—such as textiles—where responsiveness and flexibility are crucial.

Recent studies emphasize the need for collaborative scheduling models that consider inter-organizational information sharing, order synchronization, and resource optimization across multiple production nodes [7]. These models often draw from operations research, systems engineering, and artificial intelligence to handle complex multi-stage planning scenarios.

2.2. Key Technologies in Intelligent Scheduling

The advancement of intelligent manufacturing has brought forth a suite of enabling technologies that support dynamic and optimized scheduling. Notable among them are:

Manufacturing Execution Systems (MES): MES bridges the gap between enterprise-level planning systems (e.g., ERP) and shop-floor control, providing real-time data on machine status, order progress, and production capacity.

Artificial Intelligence (AI): Techniques such as genetic algorithms, ant colony optimization, and deep reinforcement learning are used to solve complex scheduling problems that are non-linear, stochastic, and high-dimensional.

Internet of Things (IoT): IoT enables real-time tracking of materials, equipment, and environmental conditions, forming the data foundation for adaptive scheduling decisions.

Edge Computing: Edge devices process data closer to the source, reducing latency and enabling rapid response to on-site disturbances or re-planning needs.

The convergence of these technologies supports the development of smart scheduling systems capable of responding autonomously to disruptions, prioritizing competing tasks, and optimizing multi-objective functions such as cost, time, and energy consumption [8].

2.3. Applications and Gaps in the Textile Industry

Despite the increasing maturity of intelligent scheduling technologies, their practical adoption in the textile industry remains limited [9]. Most existing applications are fragmented, focusing either on individual workshop automation or localized optimization, without achieving end-to-end coordination across the supply chain [10]. Additionally, challenges such as heterogeneous order types, non-standardized data interfaces, and limited algorithmic literacy continue to hinder full-scale implementation.

To provide a consolidated view, Table 1 presents a comparative summary of representative intelligent scheduling methods, highlighting their typical application domains, technical strengths, and common limitations. This overview helps to contextualize the selection of suitable approaches for textile-specific scheduling challenges.

Table 1. Comparative Summary of Representative Intelligent Scheduling Methods.

Technology / Method	Application Area	Main Features	Limitations
Genetic Algorithm (GA)	Multi-factory production, order optimization	Strong global search ability, handles complex objective functions	Slow convergence, may fall into local optima
Deep Reinforcement Learning (DRL)	Dynamic scheduling, resource allocation	Adaptive to environment changes, supports real-time optimization	Long training time, requires large datasets
Ant Colony Optimization (ACO)	Flexible job-shop scheduling	Decentralized self-organization, effective for combinatorial problems	Sensitive to parameters, influenced by initial path setup
MES-based Scheduling	Shop-floor execution and feedback control	Real-time data integration from production systems	Dependent on device-level integration and data standards
IoT + Edge Computing	Smart factory, workshop-level scheduling	Low latency, fast response, suitable for high-frequency changes	High deployment cost, limited edge-side algorithm capacity
Hybrid Systems (e.g., AI + MES)	End-to-end textile coordination	Combines multiple strengths, improves overall responsiveness	Complex system architecture, high integration requirements

3. Challenges in Textile Scheduling Coordination

Efficient scheduling coordination in the textile supply chain is challenged by structural fragmentation, data silos, and resource allocation conflicts. This section analyzes the key barriers that hinder synchronization across different production nodes and highlights the underlying complexity of dynamic scheduling within the textile industry.

3.1. Complexity of Multi-stage Supply Chain Coordination

The textile supply chain is composed of a series of interdependent stages, including spinning, weaving, dyeing and finishing, garment manufacturing, and logistics. Each stage operates under different technological conditions, objectives, and resource constraints [11]. Upstream segments often emphasize batch stability and machine throughput, while downstream operations are driven by delivery schedules and order customization. These diverging priorities create inherent tensions that complicate centralized coordination.

Moreover, the dynamic nature of interactions between stages introduces cascading effects—delays in one node (e.g., dyeing) frequently ripple downstream, resulting in inefficiencies across the entire network [12]. The absence of integrated scheduling mechanisms further contributes to misalignment, as decisions are often made in isolation by individual departments.

3.2. Information Silos and Scheduling Bottlenecks

Despite growing interest in digital transformation, many textile enterprises still operate with siloed IT infrastructures. Scheduling tasks are commonly handled independently within each plant or unit, often through legacy systems or manual spreadsheets. These disconnected workflows limit visibility, preventing planners from responding to real-time disruptions or adjusting schedules based on updated production data.

The lack of horizontal data flow across different functions impairs agility. For example, a delay in spinning may not be immediately visible to the dyeing department, leading to idle machines or misaligned resource allocation. Additionally, manually configured production plans are time-consuming and prone to errors, especially when order volumes or customer requirements change rapidly.

To highlight this issue, Figure 3 illustrates the disparity in average scheduling response times across various supply chain nodes. As shown, upstream processes such as spinning and dyeing exhibit significantly higher latency compared to downstream nodes like logistics. This imbalance further emphasizes the need for integrated and responsive scheduling frameworks.

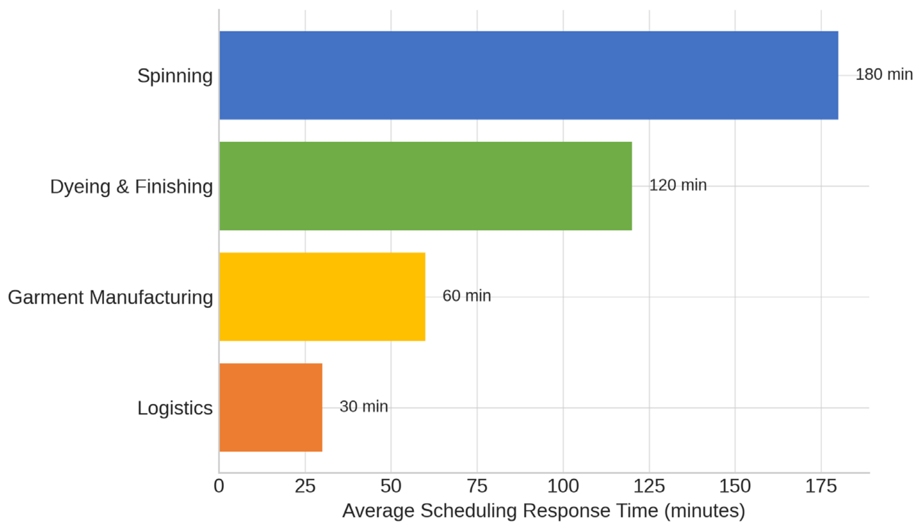

Figure 3. Response Time Across Textile Supply Chain Nodes.

3.3. Order Heterogeneity and Resource Conflicts

The textile industry is increasingly driven by customization, resulting in orders that vary in quantity, color, material, and delivery urgency. This heterogeneity leads to constant competition for limited resources—shared machines, skilled labor, or specific processing routes—making it difficult to balance utilization and efficiency.

Scheduling becomes especially difficult when multiple orders with overlapping requirements must be processed concurrently. Conflicts often emerge, forcing trade-offs between punctuality, cost, and machine usage. Furthermore, each supply chain node has unique operational characteristics, which influence its scheduling constraints and flexibility.

To better understand these differences, Table 2 presents a comparative overview of key scheduling characteristics across major textile production stages. The variation in responsiveness and predictability across nodes reinforces the necessity for node-specific strategies that are still aligned through a coordinated global schedule.

Table 2. Comparative Characteristics of Scheduling Tasks Across Textile Supply Chain Nodes.

Node	Task Flexibility	Responsiveness Requirement	Predictability	Common Constraints
Spinning Mill	Low	Medium	High	Equipment capacity, batch continuity
Dyeing & Finishing Plant	Medium	High	Medium	Color batching, chemical compatibility
Garment Manufacturing	High	High	Low	Labor availability, style-specific setup
Packaging & Logistics	Medium	Very High	Medium	Delivery deadlines, space constraints

4. Technological Adaptability and System Architecture

As textile supply chains become increasingly digitalized and distributed, the demand for intelligent, real-time scheduling grows rapidly. This section examines the technological underpinnings of smart scheduling, focusing on algorithmic adaptability, the integration of edge computing and IoT, and the architectural synthesis of MES, APS, and ERP platforms.

4.1. Adaptability of Scheduling Algorithms in the Textile Context

The textile industry presents a complex scheduling landscape: orders vary by size, color, processing steps, and urgency, while machine availability and processing times are uncertain. Conventional deterministic algorithms often fall short in such dynamic conditions. Instead, heuristic and AI-driven methods offer superior adaptability.

Among the most widely adopted are Genetic Algorithms (GA), known for their global search capabilities, and Reinforcement Learning (RL), which allows the system to learn optimal policies from interaction with dynamic environments. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) also show promise in multi-objective scheduling problems.

These algorithms vary in terms of convergence speed, solution robustness, computational overhead, and interpretability. To summarize their comparative strengths and limitations, Table 3 provides a structured overview of key attributes relevant to textile scheduling scenarios.

Table 3. Comparative Features of Mainstream Scheduling Algorithms.

Algorithm	Strengths	Limitations	Best for
Genetic Algorithm	Global optimization, robust in large spaces	Convergence speed varies, needs tuning	Complex, multi-stage scheduling
Ant Colony (ACO)	Good for discrete path finding	Can get trapped in local optima	Routing in dyeing/packing
Particle Swarm (PSO)	Fast convergence, simple implementation	May lack diversity in exploration	Resource leveling, shift allocation
Reinforcement Learning	Adaptive to real-time feedback, self-learning	High computational cost, data-hungry	Dynamic, uncertain production contexts

4.2. Integration of IoT and Edge Computing for Scheduling

Scheduling systems in the textile sector require access to real-time shop-floor data—such as machine status, operator availability, and order progress—to make timely and accurate decisions. This is where IoT (Internet of Things) and Edge Computing play critical roles.

IoT enables data collection from distributed sensors and controllers embedded in machines, storage units, and logistics vehicles. These devices continuously feed operational data to edge nodes, which process the information close to the source to minimize latency.

Edge computing ensures that critical scheduling decisions—such as rerouting urgent orders or reallocating idle machines—can be executed with minimal delay, even in the absence of a stable cloud connection. This hybrid approach improves system responsiveness, reduces bandwidth consumption, and enhances operational resilience.

4.3. Integrated System Architecture: MES + APS + ERP

To fully leverage intelligent scheduling, textile enterprises must integrate various layers of their digital infrastructure. A typical smart scheduling system is composed of three tightly connected layers:

MES (Manufacturing Execution System): Handles real-time production tracking and execution control.

APS (Advanced Planning and Scheduling): Provides algorithm-driven scheduling optimization.

ERP (Enterprise Resource Planning): Manages higher-level business processes such as order entry, procurement, and customer requirements.

These systems must communicate seamlessly through APIs or middleware, forming a closed feedback loop that links business-level planning with shop-floor execution. Figure 4 illustrates the overall system architecture, where data flows across layers to support responsive, data-driven scheduling decisions.

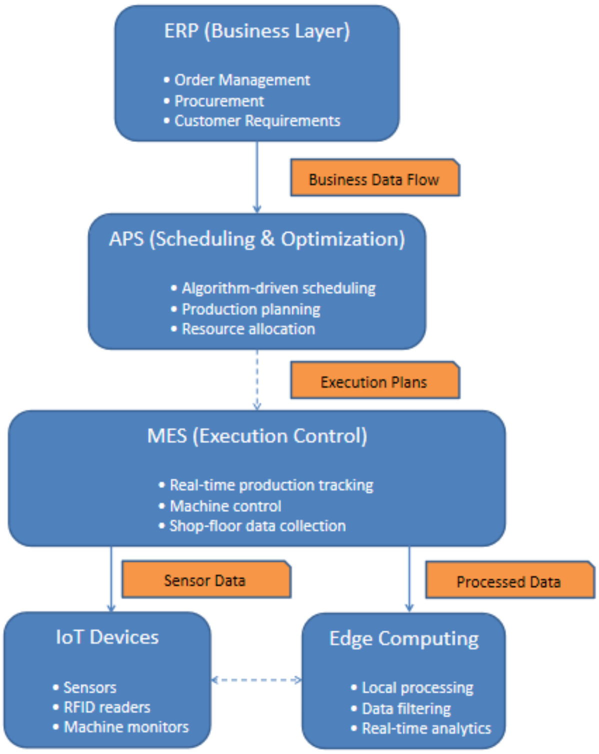

Figure 4. System Architecture of Intelligent Scheduling in Textile Supply Chains.

5. Application and Simulation Analysis

5.1. Case Study Background

This study selects a leading textile manufacturing enterprise as the research object to investigate the impact of intelligent scheduling technologies on the coordination efficiency of its supply chain. The enterprise's production process encompasses multiple key stages, including raw material procurement, spinning, weaving, dyeing and finishing, and packaging. Prior to the adoption of intelligent scheduling, the enterprise faced several operational challenges: frequent delivery delays, excessive energy consumption, and uneven equipment utilization rates. These issues significantly hindered the responsiveness and cost-efficiency of the overall textile supply chain.

5.2. Model Design

To address these challenges, an intelligent scheduling optimization model was developed with the objective of enhancing production coordination and minimizing operational inefficiencies across the supply chain. The core objective function was formulated as a weighted minimization of total production lead time and total energy consumption, expressed mathematically as:

$$\min \mathrm{Z} = \alpha \times Total\ Lead\ Time + \beta \times Total\ Energy\ Consumption$$

where α and β represent weighting coefficients that balance the priority between shortening lead times and reducing energy use, respectively.

The model includes the following constraints to reflect real-world operational limitations:

Equipment Availability Constraints: Ensuring that the working hours assigned to each piece of equipment do not exceed its maximum available capacity within the scheduling horizon.

Process Sequence Constraints: Guaranteeing that production tasks follow the predetermined sequential order of processes, thus avoiding workflow conflicts and bottlenecks.

Delivery Deadline Constraints: All production orders must be completed before their respective customer delivery deadlines to meet service level agreements.

Resource Constraints: Limitations on raw material availability and workforce capacity are strictly enforced to ensure feasible scheduling.

The model was solved using a mixed-integer linear programming (MILP) approach integrated into the simulation environment, allowing dynamic evaluation of various scheduling scenarios.

5.3. Simulation Testing and Performance Evaluation

A discrete-event simulation platform was utilized to validate the effectiveness of the intelligent scheduling model. Real production data from the enterprise over a three-month period were used to calibrate the simulation parameters, ensuring realistic representation of machine speeds, setup times, and demand patterns.

Two scenarios were compared:

Baseline Scenario: The enterprise's original scheduling approach based on manual planning and heuristic rules.

Optimized Scenario: The intelligent scheduling solution generated by the proposed optimization model.

The comparative results of these KPIs are summarized in Table 4. As shown in Table 4, the implementation of intelligent scheduling resulted in a significant reduction in average lead time from 7.8 days to 5.3 days, representing a 32.05% improvement. Similarly, energy consumption per unit decreased by 23.68%, reflecting a more energy-efficient production process. Equipment utilization rates increased by 21.46%, indicating improved allocation and usage of manufacturing resources. Additionally, the on-time delivery rate improved markedly from 74.3% to 92.7%, demonstrating enhanced reliability in meeting customer deadlines. These performance improvements, clearly evidenced in Table 4, validate the efficacy of the intelligent scheduling system in reshaping the coordination efficiency of the textile supply chain, leading to both operational and environmental benefits.

Table 4. Comparison of Key Performance Indicators.

Performance Indicator	Before Implementation	After Implementation	Improvement (%)
Average Lead Time (days)	7.8	5.3	-32.05%
Energy Consumption (kWh/unit)	15.2	11.6	-23.68%
Equipment Utilization Rate (%)	68.5	83.2	+21.46%
On-Time Delivery Rate (%)	74.3	92.7	+24.78%

The simulation results clearly demonstrate that the intelligent scheduling system significantly improves supply chain coordination. The average lead time was reduced by approximately one-third, enabling faster order fulfillment and improved customer satisfaction. Energy consumption per unit decreased by nearly 24%, reflecting enhanced operational sustainability. Furthermore, the equipment utilization rate increased by over 20%, indicating more balanced and efficient use of production resources. The on-time delivery rate also saw a notable improvement, rising from 74.3% to 92.7%, which underscores the system's positive impact on meeting customer requirements reliably.

These findings validate the role of intelligent scheduling technologies as a powerful tool for reshaping operational efficiency in the textile supply chain, promoting both economic and environmental benefits.

6. Conclusion and Implications

6.1. Research Findings and Contributions

This study systematically investigated the transformative role of intelligent scheduling technologies in enhancing coordination efficiency within the textile supply chain. Through a comprehensive case study and simulation analysis, the research demonstrated that the adoption of intelligent scheduling significantly reduces production lead times, lowers energy consumption, and improves equipment utilization rates. These improvements collectively enhance the supply chain's responsiveness and operational sustainability. The study contributes to the existing literature by integrating intelligent scheduling into textile supply chain management and quantitatively validating its benefits using real-world data. Furthermore, it highlights the potential of data-driven optimization models to address the complex scheduling challenges prevalent in traditional textile manufacturing environments.

6.2. Recommendations for Promotion

Given the demonstrated benefits, it is recommended that textile enterprises, especially small and medium-sized enterprises (SMEs), actively consider implementing intelligent scheduling solutions. For SMEs, which often face resource constraints and limited technological adoption, starting with modular and scalable intelligent scheduling tools can enable gradual improvements without large upfront investments. Industry associations and government bodies should facilitate knowledge dissemination, technical support, and financial incentives to lower barriers to adoption. Additionally, fostering partnerships between technology providers and textile firms can accelerate the diffusion of these advanced scheduling techniques throughout the sector, thereby driving collective gains in supply chain efficiency and sustainability.

6.3. Future Research Directions

Despite the promising results, several avenues for future research remain open. First, integrating green scheduling principles—aimed at minimizing environmental impacts alongside traditional efficiency metrics—can further promote sustainable production practices in the textile industry. Developing scheduling algorithms that explicitly consider carbon emissions, waste reduction, and energy source variability would be valuable. Second, exploring sustainable production planning strategies that balance economic, environmental, and social objectives across the entire textile supply chain is critical for long-term industry resilience. Finally, expanding the research scope to incorporate real-time data streams from Industry 4.0 technologies such as IoT sensors and AI-driven analytics could enhance dynamic scheduling capabilities, enabling textile enterprises to respond more agilely to market fluctuations and disruptions.

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