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An Integrated Heuristic for Make-to-Stock Production Scheduling: Balancing Efficiency and Service Level under Sequence-Dependent Setup Times

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Abstract

Make-to-stock (MTS) production systems, characterized by high product variety and complex sequence-dependent setup times, face a critical challenge in production scheduling. Conventional single-objective or rule-based scheduling methods often lead to suboptimal Overall Equipment Effectiveness (OEE) and significant inventory service-level violations. To address this gap, this study proposes a novel Hierarchical Greedy Optimization Heuristic. This multi-criteria approach systematically integrates tool group constraints, toolset compatibility, and Earliest Start Date (ESD) sequencing to determine inventory urgency, balancing operational efficiency and service reliability. The methodology is rigorously evaluated using real-world industrial data from a steel tube manufacturing system, with its performance benchmarked against two widely recognized, single-objective heuristics: the Group by Toolset Heuristic and the Order by Earliest Start Date (ESD) Heuristic. Experimental results demonstrate that the proposed heuristic consistently and significantly outperforms the benchmark methods, achieving substantially higher machine utilization (OEE) and a drastic reduction in inventory service-level violations (stockout and safety-stock violations). The findings confirm that the proposed scheduling approach is practical, scalable, and establishes a superior trade-off for sustainable MTS production environments.

Keywords
Sustainable Production Scheduling; Make-to-Stock Manufacturing; Sequence-Dependent Setup Time; Greedy Optimization; Machine Utilization; Inventory Service Level

1. Introduction
Make-to-stock (MTS) production systems are foundational to many manufacturing sectors, ensuring high product availability and rapid customer response. However, modern industrial environments are characterized by escalating product variety, frequent changeovers, and complex shared resources, making effective production scheduling a formidable challenge. In high-mix settings, such as steel tube manufacturing, hundreds of stock-keeping units (SKUs) compete for shared machines and toolsets. Without robust scheduling, this complexity often results in substantial machine idle time, energy waste, and critical inventory shortages (Madi et al. 2024).

Existing research on production scheduling has proposed various optimization and heuristic approaches to address setup times and machine constraints. However, many studies primarily focus on minimizing makespan or tardiness, with limited consideration of inventory service level in make-to-stock systems. In practice, production schedules must balance both operational efficiency and inventory reliability to prevent stockouts while maintaining high machine utilization. Advanced techniques such as metaheuristics, constraint programming, and agent-based systems have been applied to complex flow-shop and job-shop problems, including hybrid make-to-order (MTO)/MTS systems (Abdollahpour and Rezaian 2023; Chen et al. 2023)

Furthermore, studies integrating scheduling with multi-level inventory matching have highlighted the importance of aligning production with inventory targets (Zhang et al. 2015). However, much of this research focuses primarily on traditional objectives such as minimizing makespan or tardiness. A significant gap remains in developing a unified, practical, and scalable scheduling framework that explicitly balances sequence-dependent setup time minimization with the crucial metric of inventory service level, particularly in high-volume MTS environments.

To address this gap, this study proposes a novel greedy-based optimization approach for MTS production scheduling. The methodology explicitly integrates complex tooling constraints, sequence-dependent setup times, earliest-start-date (ESD) sequencing, and inventory requirements to achieve a better balance between operational efficiency and service reliability. The proposed method is rigorously validated using real industrial data from a steel tube manufacturing system, with performance assessed based on machine utilization (Overall Equipment Effectiveness: OEE) and inventory service level (stockout and safety-stock violations).

The main contributions of this study are threefold. First, a practical, scalable, greedy-based scheduling approach is developed for MTS systems, specifically designed to manage complex sequence-dependent setup and tooling constraints. Second, the method integrates production sequencing and inventory consumption patterns through ESD calculations, significantly improving inventory service-level performance. Third, the effectiveness and industrial applicability of the proposed approach are demonstrated through a real-world case study, confirming its contribution to more sustainable manufacturing operations.

2. Literature Review

Make-to-stock (MTS) production systems are widely used in industries that require high product availability and fast customer response. However, increasing product variety, complex routing, and shared resources have significantly increased scheduling complexity. Recent studies emphasize that traditional rule-based or manual scheduling approaches are no longer sufficient for modern manufacturing systems, particularly in high-mix, capacity-constrained environments.

Several researchers have proposed heuristic and agent-based optimization approaches to address MTS scheduling challenges. Madi et al. (2024) developed an agent-based heuristic optimization model for MTS connector plate manufacturing systems, demonstrating improved production efficiency and adaptability in complex environments. Similarly, Bagheri et al. (2022) applied an agent-based approach to master production scheduling, highlighting the effectiveness of decentralized decision-making in handling large-scale scheduling problems.

Integrated and multi-stage scheduling has also received significant attention. Dan et al. (2025) proposed an integrated optimization framework that simultaneously considers production scheduling and transportation, demonstrating that cross-stage coordination can significantly enhance system performance. In hybrid production environments, Chen et al. (2023) investigated flow-shop scheduling for combined make-to-stock and make-to-order systems in distributed precast concrete production, highlighting the importance of balancing different production policies.

Advanced optimization techniques, such as metaheuristics and hybrid approaches, have been widely applied to complex scheduling problems. Abdollahpour and Rezaian (2023) proposed two new metaheuristic algorithms for no-wait flexible flow shop scheduling under mixed make-to-order and make-to-stock policies, highlighting the effectiveness of metaheuristics in handling highly constrained production environments. In addition, Castro and Godinho-Filho (2022) developed a dispatching method based on particle swarm optimization (PSO) for make-to-availability systems, demonstrating that intelligent heuristic-based dispatching rules can significantly improve scheduling performance in capacity-constrained environments.

Particle swarm optimization has also been applied to scheduling problems that integrate inventory considerations. Zhang et al. (2015) proposed a multi-level inventory-matching and order-planning model for hybrid make-to-order and make-to-stock steel production systems using PSO. Their results emphasize the importance of jointly considering production scheduling and inventory planning to improve service level and system responsiveness.

Although the reviewed studies demonstrate significant advances in scheduling optimization for MTS and hybrid production systems, most focus primarily on complex optimization or metaheuristic frameworks, which may be difficult to implement and maintain in real industrial settings. Moreover, limited attention has been paid to sequence-dependent setup times, machine utilization (OEE), and inventory service level within a unified, practical scheduling framework. This study addresses this gap by proposing a greedy-based scheduling approach that explicitly considers sequence-dependent setup times, machine utilization, and inventory service level, validated using real industrial data.

3. Methods

A This study proposes a greedy-based scheduling methodology for make-to-stock production systems with sequence-dependent setup times and complex tooling constraints. The objective of the methodology is to improve machine utilization and inventory service level while maintaining practical applicability for large-scale industrial environments.

3.1 Problem Description

The production system considered in this study consists of multiple parallel machines producing a large number of SKUs under make-to-stock conditions. Each SKU requires a specific toolset, which is organized into tool groups. Machines are compatible with specific toolsets, and setup times between toolsets are sequence-dependent, meaning the setup duration varies with the production sequence. Demand is continuous, and inventory levels must be maintained above zero and above minimum safety stock to ensure acceptable service levels.

The scheduling problem involves determining the production sequence, machine assignment, and production quantity for each SKU, while accounting for machine availability, tool compatibility, sequence-dependent setup times, and inventory constraints (Table 1).

3.2 Parameters and Notations

Table 1. summarizes the parameters and notations used in the proposed scheduling methodology.

Parameter	Description
i	Index of SKU, $i = 1, 2, \dots, N$
m	Index of machine, $m = 1, 2, \dots, M$
g	Tool group index
t	Toolset index
D_i	Daily demand of SKU i (pcs/day)
I_i^0	Current inventory level of the SKU i
I_i^{min}	Minimum (safety) stock level of SKU i
I_i^{max}	Maximum stock level of SKU i
Q_i	Production quantity of SKU i
ESD_i	Earliest start date of SKU i
ESD_g^{TG}	Earliest start date of Tool Group g
ESD_t^{TS}	Earliest start date of Toolset t
P_{im}	Production rate of SKU i on the machine m (pcs/hour)
$ST_{t,t'}^m$	Sequence-dependent setup time from the toolset t to i' on machine m
A_m	Available working time of the machine m
WT_m	Actual working (processing) time of the machine m (hours)
OEE_m	Overall Equipment Effectiveness (machine utilization) of the machine m(%)
OEE_{avg}	Average Overall Equipment Effectiveness across all machines (%)
PSD	Planning Start Date
H	Planning horizon (days)
F	Frozen period (days)
SL_i^{zero}	Stockout service level $(\text{inventory} \geq 0)$ of SKU i (%)

SL_i^{min}	Safety stock service level (inventory ≥ minimum) of SKU i (%)

3.3 Performance Measures

Two key performance indicators are used to evaluate the scheduling performance: Overall Equipment Effectiveness (OEE) and Inventory Service Level.

3.3.1 Machine Utilization (Overall Equipment Effectiveness: OEE)

In this study, OEE is used to measure machine utilization by focusing on **time-based effectiveness**, which is appropriate for production scheduling analysis. OEE is calculated as:

$$OEE_m(\%) = \frac{WT_m}{A_m} \times 100$$

where:

- $WT_m$is the total productive processing time of the machine m, excluding setup time, maintenance, and idle time.
- $A_m$is the total available operating time of the machine $m$during the planning horizon.

The average OEE across all machines is calculated as:

$$OEE_{avg} = \frac{1}{M} OEE_m$$

A higher OEE indicates better machine utilization and more efficient use of production resources.

3.3.2 Inventory Service Level Metrics

Inventory service level is evaluated using two complementary time-based performance indicators to quantify the reliability of the make-to-stock system: the frequency of stockouts and the frequency of safety-stock violations.

(1) Stockout Frequency

Stockout Frequency measures the proportion of days during the planning horizon where the inventory level of SKU *i* falls below zero:

$$SL_i^{zero}(\%) = \left(\frac{Days(I_i < 0)}{H}\right) \times 100$$

where:

- $Days(I_i < 0)$is the number of days the SKU i has had inventory below zero.
- H is the planning horizon in days.

(2) Safety Stock Violation Frequency

Safety Stock Violation Frequency measures the proportion of days during the planning horizon where the inventory level of SKU *i* falls below its minimum (safety) stock level:

$$SL_i^{min}(\%) = \left(\frac{Days(I_i < I_i^{min})}{H}\right) \times 100$$

Lower values for both $SL_i^{zero}(\%)$ and $SL_i^{min}(\%)$ indicate superior inventory reliability and a reduced risk of shortages.

3.4 Hierarchical Greedy Optimization Heuristic

The proposed methodology employs a Hierarchical Greedy Optimization Heuristic designed to sequence production for Make-to-Stock (MTS) systems, balancing setup time reduction with inventory requirements. The approach is executed through the following sequential decision steps (Figure 1):

1. **Tool Group Prioritization:**
   All Stock-Keeping Units (SKUs) are initially grouped by their required tool group. This primary grouping minimizes major, time-consuming setup changes between different tool groups.
2. **Earliest Start Date Calculation**
   To incorporate inventory urgency and the risk of stockout, the Earliest Start Date (ESD_i) for each SKU is calculated. This metric estimates the number of days the current inventory level (I_i^0) can sustain demand (D_i) before falling below the minimum (safety) stock (I_i^{min}):

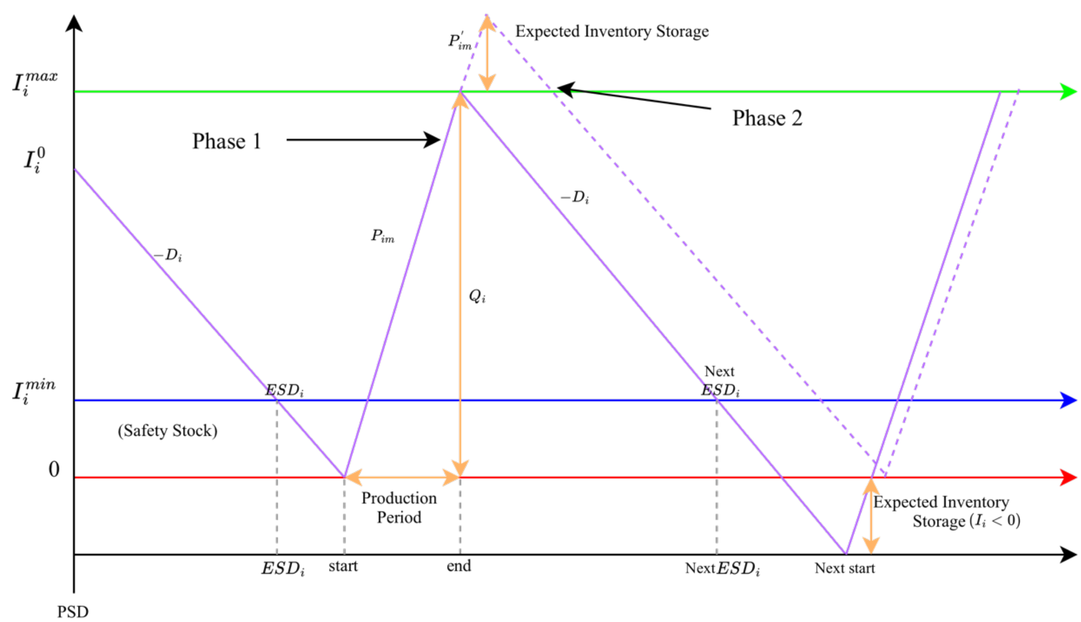
$$ESD_i = PSD + \frac{I_i^0 - I_i^{min}}{D_i}$$

A lower ESD_i number signifies a more critical need for immediate production.

3. **Toolset-Based Sequencing and Refinement:**
   Within the prioritized tool group, Stock-Keeping Units (SKUs) are further grouped by toolset. The toolsets within this group are then ordered by their calculated Earliest Start Date (ESD). The production sequence of SKUs within the selected toolset is finally determined by sorting according to a predefined machine-specific criterion, such as thickness, to minimize minor, intra-toolset setup times.

4. **Machine Assignment**
   For the prioritized toolset sequence, compatible machines are identified. The machine with the earliest available time is selected for assignment to the next production batch, following a greedy policy to maximize machine utilization.

5. **Production Quantity Determination:**
   The production quantity (Q_i) for an assigned SKU is determined by balancing the daily demand (D_i), production rate (P_{im}) and maximum inventory level (I_i^{max}). During Phase 1 (Production Sequence Construction Phase), shown by the solid purple line, production is triggered at the "start" point to restore stock levels toward the target I_i^{max} line, ensuring that (Q_i) is optimized for machine capacity and the planning horizon. This sequence is then refined in Phase 2 (Inventory Shortage Improvement Phase), where the dashed purple lines identify potential risks—such as expected inventory overflows (P'_{im}) or shortages where $I_i < 0$. By analyzing these deviations, the system improves the schedule, adjusting production timing to pull the inventory trajectory back into the stable operating zone established in the construction phase (Figure 1).



Phase 1: Production sequence construction phase,   Phase 2: Inventory shortage improvement phase

Figure 1. Inventory Dynamics and Production Cycle Diagram

3.5 Benchmark Scheduling Methods and Comparison Heuristics

To rigorously evaluate the efficacy of the proposed Hierarchical Greedy Optimization Heuristic, its performance is benchmarked against two widely recognized scheduling priority rules. These rules represent single-objective heuristics: one prioritizing operational efficiency (setup reduction) and the other prioritizing inventory service level (stockout avoidance).

3.5.1 Group by Toolset Heuristic

As illustrated in Figure 2, this heuristic creates a hierarchical scheduling structure where individual SKUs are clustered into ToolSets to streamline production. The callout for Machine 01 demonstrates this by grouping SKUs (e.g., SKU TH 01 through TH 04) within ToolSet 25, separated only by minor 30-minute intervals. However, the diagram also captures the trade-off mentioned in the heuristic: while switching between ToolSets within the same group requires a moderate "toolset setup" (orange block), transitioning between different tool groups—such as moving from Tool Group 07 to Tool Group 09—results in a substantial "Tool Group setup" (pink block). This visualizes how sequence dependence can lead to significant machine downtime if the heuristic prioritizes toolsets that necessitate a full group changeover.

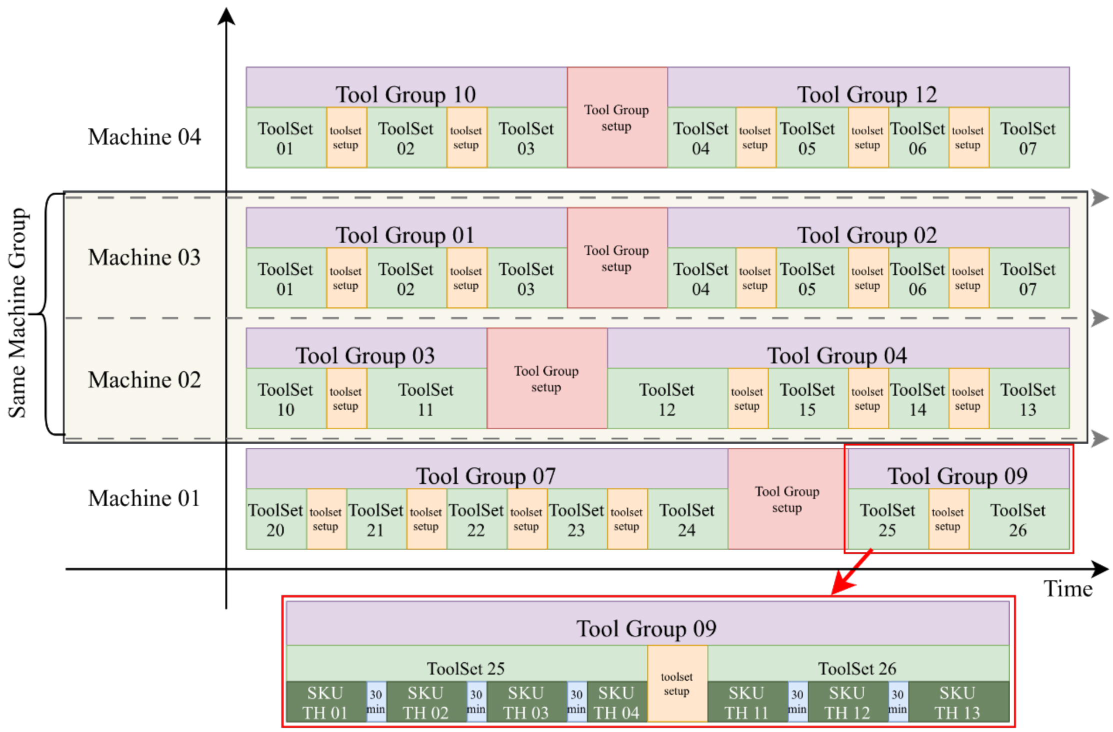


Figure 2. Hierarchical Production Scheduling and Setup Structure in machine group

3.5.2 Order by Earliest Start Date (ESD) Heuristic

The Order by Earliest Start Date (ESD) Heuristic is an inventory-driven priority rule designed to maximize service level performance. This method prioritizes all pending production orders solely by ascending their calculated Earliest Start Date (ESD_i). The SKU with the lowest ESD_i, indicating the greatest risk of stockout or safety-stock violation, is scheduled next. While this approach is effective in addressing immediate inventory shortages, it completely disregards the constraints imposed by sequence-dependent setup times and tooling compatibility, often leading to frequent, time-consuming tool changeovers and significantly lower machine utilization.

3.6 Adaptive Mitigation of Residual Stockout Risks

Although the proposed Hierarchical Greedy Optimization Heuristic substantially improves inventory service levels, a limited number of Stock-Keeping Units (SKUs) may still experience residual stockouts in highly constrained scenarios where cumulative demand exceeds available production capacity and sequence-dependent setup times restrict scheduling flexibility. In such cases, production sequencing alone may be insufficient to fully prevent inventory depletion before the next feasible production opportunity. To address this limitation, an adaptive post-scheduling adjustment is applied by re-evaluating inventory trajectories after production completion and identifying SKUs projected to fall below zero inventory levels. The production quantities of these affected SKUs are then selectively increased, within the remaining available capacity, to ensure non-negative inventory throughout the inter-production period, without altering the established production sequence or machine assignments. This refinement complements the sequencing logic by enhancing service-level robustness while preserving machine utilization efficiency, thereby strengthening the practical applicability of the proposed framework in real-world make-to-stock production environments.

4. Test Data

The proposed scheduling approach is evaluated using real industrial data obtained from a steel tube manufacturing system operating under make-to-stock conditions. The production system is characterized by high product variety, multiple parallel machines, and complex tool and setup relationships. The dataset reflects actual operational conditions and is suitable for validating the practicality and scalability of the proposed method.

4.1 Production System Description

The production system produces several hundred SKUs of steel tubes with different dimensions and thicknesses. Production is carried out on multiple parallel machines, each with a specific toolset. Toolsets are grouped into tool groups, and sequence-dependent setup times occur when switching between different toolsets on the same machine. Setup times vary significantly by sequence and machine, ranging from short durations within the same tool group to several hours when changing between tool groups. Demand for each SKU is continuous and varies across products. Inventory is managed under a make-to-stock policy, with defined minimum (safety) stock levels. Production planning is performed over a finite planning horizon with a frozen period during which schedules cannot be modified.

4.2 Experimental Design and Dataset Configurations

To rigorously evaluate the robustness and scalability of the proposed scheduling approach, three distinct dataset configurations—Small, Medium, and Large—are employed. As summarized in Table 2, these datasets vary in key dimensions, including the number of SKUs, machines, and toolsets, as well as the planning horizon and frozen period, simulating different industrial scales and complexities.

Table 2. Test Data Configuration

Dataset	Number of SKUs	Number of Machines	Number of Toolsets	Planning Horizon (days)	Frozen Period (days)
Small	750	6	76	30	7
Medium	752	10	77	60	14
Large	790	14	82	120	21

Each dataset is tested using three scheduling methods: the proposed Hierarchical Greedy Optimization Heuristic, the Group-by-Toolset Heuristic, and the Order-by-Earliest-Start-Date (ESD) Heuristic. All methods are evaluated under identical demand profiles, machine availability, and planning horizons to ensure fair comparison. Performance is assessed using machine utilization (OEE) and inventory service-level metrics, including stockout and safety-stock violations.

4.3 Setup Time and Processing Characteristics

Production rates vary by SKU-machine combination and are measured in pieces per hour. Setup times are sequence-dependent and differ across machines and toolsets. When the same tool group is used, setup times are relatively short; however, switching between tool groups can result in long setup times. These setup characteristics significantly influence machine utilization and production efficiency and are explicitly considered in the scheduling algorithm.

5. Results and Discussion

This section presents and discusses the performance of the proposed greedy-based scheduling approach compared with two benchmark methods: Group by Toolset and Order by Earliest Start Date (ESD). The evaluation focuses on two key performance indicators: machine utilization (OEE) and inventory service level, including stockout (below zero) and safety stock violations.

5.1 Machine Utilization (OEE)

Table 3 summarizes the machine utilization results across different dataset sizes. The proposed method consistently achieves the highest OEE compared to the benchmark methods.

Table 3. Comparison of Machine Utilization (OEE)

Dataset	Phase	Hierarchical Greedy Optimization Heuristic	Group by Toolset Heuristic	Order by Earliest Start Date (ESD) Heuristic
Small	Phase 1	67.20	67.52	62.09
	Phase 2	67.43	67.52	62.09
Medium	Phase 1	61.07	68.16	65.15
	Phase 2	68.67	68.16	65.15
Large	Phase 1	31.76	63.49	58.37
	Phase 2	31.69	63.37	57.94

The proposed approach improves machine utilization by reducing unnecessary idle time and minimizing frequent tool changes. By grouping SKUs by tool groups and toolsets and selecting machines with the earliest available times, the algorithm creates more stable production sequences. In contrast, the Order-by-ESD method often causes machine interruptions due to frequent tool changes, resulting in the lowest utilization. The Group by Toolset method partially reduces setup times but lacks inventory-aware sequencing, resulting in only moderate improvement in utilization.

5.2 Inventory Service Level Performance

Inventory service-level performance is evaluated based on the number of days with inventory below zero (stockout) and below the minimum safety stock. Table 4 presents a comparative summary of service level performance.

Table 4. Inventory Service Level Comparison

Dataset	Method	Phase	Stockout			Safety Stock Violation		
			Number of Product	Number of Day	Frequency (%)	Number of Product	Number of Day	Frequency (%)
Small	**Hierarchical Greedy Optimization Heuristic**	Phase 1	35	9	69.04	43	17	39.63
		Phase 2	30	8	71.84	44	16	42.35
	Group by Toolset Heuristic	Phase 1	32	8	70.37	44	16	42.21
		Phase 2	32	8	70.37	44	16	42.21
	Order by Earliest Start Date (ESD) Heuristic	Phase 1	39	10	64.71	44	18	35.59
		Phase 2	39	10	64.71	44	18	35.59
Medium	**Hierarchical Greedy Optimization Heuristic**	Phase 1	36	21	63.94	47	34	41.89
		Phase 2	40	23	62.08	48	35	41.01
	Group by Toolset Heuristic	Phase 1	39	20	65.98	48	35	41.50
		Phase 2	39	20	65.98	48	35	41.50
	Order by Earliest Start Date (ESD) Heuristic	Phase 1	38	19	68.75	48	35	41.50
		Phase 2	38	19	68.75	48	35	41.50

Large	**Hierarchical Greedy Optimization Heuristic**	Phase 1	34	50	58.17	44	61	49.58
		Phase 2	34	50	58.17	44	61	49.48
	Group by Toolset Heuristic	Phase 1	32	44	63.43	45	56	53.57
		Phase 2	28	42	64.79	44	55	54.26
	Order by Earliest Start Date (ESD) Heuristic	Phase 1	33	41	65.70	46	56	53.53
		Phase 2	33	41	65.70	46	56	53.53

The proposed method significantly reduces both stockout days and safety stock violations by aligning production timing with inventory consumption patterns. The integration of the earliest start date (ESD) with tool-based sequencing enables earlier production of critical SKUs, thereby improving service-level reliability. The Group by Toolset method improves setup efficiency but still results in service level issues due to insufficient inventory prioritization. The Order-by-ESD method, although inventory-driven, ignores setup constraints, leading to inefficient production sequences and frequent shortages.

5.3 Trade-off Between Efficiency and Service Level

The results demonstrate that the proposed method achieves a better balance between operational efficiency and inventory reliability. High machine utilization does not come at the expense of service level performance. Instead, the proposed approach maintains stable inventory levels while improving machine efficiency, supporting sustainable production objectives.

However, despite the overall improvement, some SKUs still experience inventory levels below zero, particularly those with highly volatile demand or long setup times. This indicates that while scheduling improvements are effective, further enhancements are necessary, including recalculating stockout quantities and adjusting production volumes.

5.4 Managerial and Industrial Implications

From an industrial perspective, the proposed scheduling approach provides a practical decision-support tool for production planners. The method is computationally efficient, easy to implement, and adaptable to real-world constraints such as tool compatibility and sequence-dependent setup times. Improved machine utilization reduces energy consumption and operational waste, while enhanced service-level performance increases customer satisfaction and system reliability.

6. Conclusion

This study successfully addressed the critical challenge in high-mix, make-to-stock (MTS) production environments: effectively balancing operational efficiency with inventory service-level reliability under conditions of high product variety and complex sequence-dependent setup times. We proposed a novel, multi-criteria Hierarchical Greedy Optimization Heuristic that systematically integrates tooling constraints and sequence-dependent setups with inventory urgency, quantified via the Earliest Start Date (ESD).

The rigorous experimental validation, utilizing real-world industrial data from a steel tube manufacturing system, demonstrated the compelling superiority of the proposed approach. When benchmarked against two widely recognized single-objective heuristics—the Group by Toolset Heuristic (efficiency-driven) and the Order by ESD Heuristic (inventory-driven)—the Hierarchical Greedy Optimization Heuristic consistently and significantly outperformed both. Specifically, the method achieved substantially higher Overall Equipment Effectiveness (OEE) while simultaneously delivering a drastic reduction in inventory service-level violations, including both stockout and safety-stock shortages.

In conclusion, this research confirms that the proposed integrated scheduling framework establishes a superior trade-off between machine utilization and inventory reliability. The resulting heuristic is not only practical and scalable for real-world industrial implementation but also serves as an effective decision-support tool, contributing to more efficient, reliable, and sustainable MTS production operations.

7. Future Work

Although the proposed scheduling approach demonstrates substantial improvements in machine utilization and inventory service-level performance, a limited number of Stock-Keeping Units (SKUs) may still experience negative inventory levels, particularly under conditions of high demand variability or prolonged sequence-dependent setup times. This limitation indicates that further methodological enhancements are necessary to fully eliminate residual stockouts in capacity-constrained make-to-stock production systems.

In the current framework, production quantities are determined primarily based on daily demand and the targeted number of inventory coverage days. Future research will extend this formulation by explicitly incorporating the expected time to the next production opportunity for each SKU, which is influenced by machine capacity, production sequences, and competing SKUs assigned to the same machine. By accounting for the anticipated length of the inter-production interval, production quantities can be more accurately adjusted to ensure inventory sufficiency throughout the entire replenishment cycle.

Additionally, future work will explore alternative scheduling optimization paradigms to further enhance both operational efficiency and service-level reliability. Advanced approaches such as constraint programming and metaheuristic algorithms will be investigated to address the increasing complexity of large-scale scheduling problems involving sequence-dependent setup times, tooling constraints, and dynamic inventory requirements. These methods may complement or extend the proposed greedy-based heuristic by providing improved solution quality under highly constrained or stochastic conditions.

Together, these research directions are expected to strengthen the robustness, adaptability, and scalability of make-to-stock production scheduling systems, contributing to more resilient and sustainable manufacturing operations in complex industrial environments.

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