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A Multi-Criteria Decision Framework for Dynamic Work Order Prioritization in Multi-Constrained Manufacturing Environments

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Abstract

Modern manufacturing systems operate in increasingly dynamic and uncertain environments, making intelligent and adaptive decision-making essential for effective production control. One of the key challenges in such systems is dynamic work order prioritization within multi-constrained settings, where fluctuating demand, shared resources, machine breakdowns, workforce limitations, and conflicting performance objectives must be managed simultaneously. Traditional dispatching rules, such as First-Come-First-Serve (FCFS) and Shortest Processing Time (SPT) are often inadequate, as they focus on single performance metrics and overlook broader operational and strategic factors. To address this limitation, this study presents a structured multi-criteria decision-making (MCDM) framework for dynamic work order prioritization in an electronic manufacturing context. The proposed framework integrates the Analytic Hierarchy Process (AHP) to determine the relative importance of decision criteria and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank competing work orders. Orders are evaluated based on multiple factors, including due date urgency, processing time, setup requirements, customer priority, profit contribution, resource availability, and work-in-process levels. A dynamic updating mechanism continuously recalculates priority scores as system conditions evolve, enabling real-time responsiveness to disruptions and demand variability. The framework was implemented and validated using a simulated multi-product electronic manufacturing system with capacity constraints and stochastic events, demonstrating improved on-time delivery, reduced average flow time, better machine utilization, and more balanced workload distribution compared to conventional single-rule dispatching approaches, thereby offering a scalable and effective decision-support solution for complex manufacturing environments.

Keywords
Multi-Criteria Decision Making, Work Order Prioritization, Manufacturing Systems, Dynamic Scheduling, Productivity Improvement

1. Introduction
1.1 Background
Deciding which order to process next is one of the most frequent and impactful decisions made on a manufacturing shop floor. Each choice sets off a cascade of consequences: it affects when subsequent orders will finish, whether machines remain productive, and ultimately whether customer promises are kept. Production managers face this dilemma daily as they look at a pool of pending orders, each with its own due date, processing requirements, customer importance, and profitability. In modern factories, where demand fluctuates unpredictably, resources are shared, machines break down without warning, and multiple performance goals compete, the simple rules that served industry for decades are no longer adequate.

Traditional dispatching rules such as First-Come-First-Serve (FCFS) and Shortest Processing Time (SPT) are often inadequate, as they focus on single performance metrics and overlook broader operational and strategic factors (Mohan et al. 2019). FCFS treats all orders equally based solely on arrival time, disregarding differences in customer importance, profit margins, or delivery urgency. SPT prioritizes jobs with minimal processing durations, which effectively reduces work-in-process inventory but frequently causes high-value or time-sensitive orders to experience excessive delays (Zhang et al. 2022). Neither approach accounts for the interconnected nature of modern production systems where sequencing decisions at one workstation propagate effects throughout the entire facility.

The electronics manufacturing sector exemplifies these challenges with particular intensity. High-mix low-volume production runs, frequent changeovers, capital-intensive equipment, and stringent quality requirements characterize this domain. Customer orders arrive stochastically with distinct specifications, delivery commitments, and contractual obligations. Shared resources must accommodate multiple product lines simultaneously, creating competition for bottleneck operations. Unscheduled machine downtime disrupts planned sequences without warning. Workforce availability fluctuates due to training requirements, absenteeism, or skill mismatches. Under such conditions, simplistic dispatching rules consistently underperform because they cannot capture the multidimensional nature of prioritization decisions (Kuhnle et al. 2021).

Multi-Criteria Decision Making (MCDM) methodologies offer systematic frameworks for evaluating alternatives across multiple conflicting dimensions simultaneously. Unlike single-criterion approaches, MCDM techniques explicitly acknowledge that real-world decisions involve trade-offs between competing objectives and seek to identify solutions that appropriately balance these trade-offs (Tuncel and Aydin 2021). The Analytic Hierarchy Process (AHP), formalized by Saaty (2008), enables decision-makers to derive quantitative importance weights for qualitative criteria through structured pairwise comparisons. This method captures domain expertise while maintaining mathematical rigor through consistency verification procedures. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), extensively documented by Behzadian et al. (2012), ranks alternatives based on geometric proximity to an ideal solution and distance from a negative-ideal reference point. This approach produces intuitively interpretable results that align with human reasoning patterns.

However, most existing MCDM applications in production scheduling operate in static modes where criterion weights remain fixed and job evaluations occur only at order release (Kumar et al. 2020). Such approaches cannot respond to evolving shop floor conditions, emerging disruptions, or shifting priorities. A machine failure occurring mid-shift fundamentally alters the relative desirability of pending jobs, yet static systems continue operating with outdated rankings. New orders arriving with urgent delivery requirements necessitate immediate integration into the decision framework, but static methods defer evaluation until scheduled recalculation points. This research addresses these limitations by developing a dynamic MCDM framework that continuously updates work order priorities in response to evolving system conditions, enabling genuine real-time responsiveness to disruptions and demand variability (Vieira et al. 2003).

1.2 Objectives
This study pursues six interconnected tasks to serve the core objective. First, to develop a structured multi-criteria decision-making framework integrating AHP and TOPSIS for dynamic work order prioritization in multi-constrained

manufacturing environments capable of simultaneously handling conflicting performance objectives. Second, to establish a comprehensive evaluation criteria set encompassing due date urgency, processing time, setup requirements, customer priority, profit contribution, resource availability, and work-in-process levels that collectively captures the multidimensional nature of prioritization decisions. Third, to design and implement a dynamic updating mechanism that continuously recalculates priority scores as system conditions evolve, including new order arrivals, machine breakdowns, order completions, and periodic intervals, thereby enabling real-time responsiveness to disruptions and demand variability. Fourth, to validate the proposed framework through discrete-event simulation of a multi-product electronic manufacturing system incorporating realistic capacity constraints, stochastic processing times, random machine failures, and variable demand patterns. Fifth, to quantify performance improvements in on-time delivery rates, average flow times, machine utilization levels, and workload distribution balance compared to conventional single-rule dispatching approaches including FCFS and SPT. Sixth, to provide practitioners with a scalable and effective decision-support solution suitable for complex manufacturing environments.

2. Literature Review

The academic literature contains extensive documentation of dispatching rule development and evaluation spanning several decades. Mohan et al. (2019) conducted a comprehensive review of dynamic job shop scheduling techniques, examining over one hundred distinct rules and their performance characteristics across multiple metrics. Their analysis confirmed that no single rule achieves superior performance across all evaluation criteria simultaneously. Rules that minimize flow times typically increase tardiness, while those prioritizing due dates often sacrifice utilization efficiency. Zhang et al. (2022) evaluated traditional dispatching rules within Industry 4.0 contexts and found that conventional approaches cannot adequately handle multiple conflicting objectives characteristic of smart manufacturing environments. Their research demonstrated that FCFS, despite its simplicity and perceived fairness, performs poorly when customer priorities vary significantly or when capacity constraints create bottlenecks. SPT, while effective for reducing work-in-process inventory, frequently causes high-value orders with longer processing times to experience excessive delays, potentially damaging customer relationships and reducing profitability. Kuhnle et al. (2021) observed that traditional dispatching rules emerged from an era of relatively stable production environments with limited product variety and predictable demand patterns. Contemporary manufacturing systems bear little resemblance to these historical contexts, featuring high product mix variability, frequent changeovers, and constant demand fluctuations. Their analysis argued that rule-based approaches cannot capture the complex interdependencies characteristic of modern production systems where decisions at one workstation propagate throughout the entire facility.

Tuncel and Aydin (2021) provided a comprehensive state-of-the-art review of multi-criteria decision-making applications in production scheduling, documenting increasing adoption of hybrid approaches combining multiple MCDM methods. Their analysis revealed that while MCDM techniques have been extensively applied to strategic manufacturing decisions such as supplier selection, facility layout, and technology investment, their application to operational scheduling decisions remains relatively limited. Yazdi et al. (2020) demonstrated that single-criterion approaches prove insufficient when manufacturing decisions involve multiple conflicting objectives with different measurement scales and units. Their work developed an integrated MCDM framework for manufacturing strategy selection incorporating both quantitative performance metrics and qualitative strategic considerations, highlighting the importance of capturing expert judgment through structured elicitation methods while maintaining mathematical rigor through consistency verification procedures. Chen and Wang (2019) applied MCDM techniques specifically to production scheduling optimization, developing a hybrid approach combining weighted scoring with outranking methods. Their framework evaluated jobs based on multiple criteria including due dates, processing times, and customer priorities, generating ranked sequences for shop floor execution. However, their approach operated in static mode with fixed criterion weights and did not incorporate mechanisms for responding to real-time disruptions or changing conditions.

Saaty (2008) provided an updated exposition of the Analytic Hierarchy Process, emphasizing its applicability to complex decision environments where both quantitative data and qualitative judgments require integration. The methodology enables decision-makers to decompose complex problems into hierarchical structures, perform pairwise comparisons to establish relative importance, and verify judgment consistency through mathematical procedures. AHP has been widely adopted in manufacturing applications including technology selection, supplier evaluation, and process improvement prioritization. Behzadian et al. (2012) conducted an extensive survey of TOPSIS applications, documenting the methodology's evolution and diverse implementations across multiple domains. TOPSIS appeals to practitioners because its underlying logic aligns with human reasoning patterns and its computational requirements remain modest even for large alternative sets. The technique identifies compromise solutions by measuring geometric distances from ideal and negative-ideal reference points, providing intuitively interpretable rankings that facilitate decision-making. Kumar et al. (2020) developed a fuzzy AHP and TOPSIS based approach for job selection in flexible manufacturing systems, addressing the uncertainty inherent in manufacturing environments through fuzzy set theory. Their framework evaluated jobs based on multiple criteria including processing times, setup requirements, and due dates, generating rankings for production sequencing. The research demonstrated the approach on a simulated flexible manufacturing cell, showing improved performance compared to single-criterion rules. Yazdi et al. (2020) integrated AHP and TOPSIS for manufacturing strategy selection, demonstrating how the combined methodology captures both strategic priorities and operational constraints. Their framework first used AHP to establish criterion weights based on executive judgments, then applied TOPSIS to evaluate alternative strategies against these weighted criteria, emphasizing the importance of sensitivity analysis to verify result robustness across reasonable input parameter variations.

Vieira et al. (2003) established the foundational framework for understanding rescheduling strategies, policies, and methods in manufacturing systems. Their work defined rescheduling as the process of updating existing production schedules in response to disruptions or other changes, establishing standard definitions and classification schemes that remain authoritative. The research distinguished between predictive scheduling, which creates schedules before execution, and reactive scheduling, which modifies schedules in response to unexpected events. Kuhnle et al. (2021) conducted a systematic review of reinforcement learning applications for adaptive scheduling in manufacturing, documenting the emergence of machine learning approaches for dynamic decision-making. Their analysis revealed that while reinforcement learning can achieve impressive performance in simulated environments, these black-box models often lack interpretability and require extensive training data that may not be available in real manufacturing settings. Recent research has begun exploring hybrid approaches combining the transparency of MCDM methods with the adaptability of dynamic scheduling frameworks. However, such integrated approaches remain relatively rare in the literature, with most studies focusing either on static MCDM applications or on black-box machine learning methods. This gap provides the motivation for developing a dynamic MCDM framework that maintains interpretability while achieving real-time responsiveness to changing conditions.

Recent IEOM conference research has also examined advanced scheduling problems in flexible and distributed manufacturing systems. Studies on Job Shop Scheduling (JSP), Flexible Job Shop Scheduling (FJSP), and Distributed Flexible Job Shop Scheduling (DFJSP) have demonstrated the importance of simultaneously considering production efficiency, resource utilization, due-date performance, and energy consumption in complex manufacturing environments. Energy-aware scheduling approaches have incorporated sustainability objectives alongside traditional performance measures, highlighting the growing need for decision-support frameworks capable of balancing operational and strategic criteria. While these studies primarily focus on optimization-based scheduling and sequencing decisions, they reinforce the importance of multi-criteria prioritization in dynamic production environments. The present study complements this stream of research by focusing on real-time work order prioritization using an interpretable AHP-TOPSIS framework that can dynamically respond to changing shop-floor conditions while also accommodating additional objectives such as energy consumption.

Three significant gaps emerge from the literature analysis. First, most MCDM-based job prioritization models operate in static modes and cannot respond to real-time changes in shop floor conditions. Criterion weights remain fixed throughout the scheduling horizon, and job evaluations occur only at order release, ignoring the dynamic nature of manufacturing environments where machine status, queue lengths, and relative priorities shift continuously. Second, existing frameworks seldom incorporate real-time shop floor constraints such as current machine availability, evolving work-in-process levels, or emerging bottleneck conditions. These dynamic factors fundamentally influence the relative desirability of competing jobs, yet static systems cannot capture their effects. A job that appeared attractive at order release may become problematic hours later when a key machine fails or queues build up at subsequent workstations. Third, validation studies rarely include rigorous statistical comparisons against simple dispatching rules within stochastic environments that realistically model disruptions and variability. Many studies demonstrate improvements in deterministic settings but fail to establish that benefits persist when randomness and uncertainty characterize the operating environment, limiting confidence in practical applicability.

In addition, although recent research in JSP, FJSP, DFJSP, and energy-aware manufacturing scheduling has advanced optimization methods for production planning and sequencing, relatively limited attention has been given to dynamic

work-order prioritization frameworks that combine real-time responsiveness, multi-criteria decision-making, and managerial interpretability.
This study addresses these gaps by developing a dynamic AHP-TOPSIS framework that continuously updates job priorities at decision epochs, explicitly incorporates real-time resource availability and work-in-process measurements, and validates performance through rigorous statistical analysis within a stochastic simulation environment.

3. Methods
The proposed framework is validated through a discrete-event simulation of a multi-product electronics assembly line. To ensure the conclusions are robust and reproducible, the validation is structured as four interconnected experiments. Each experiment isolates a specific aspect of the framework's performance, enabling a clear understanding of the underlying mechanisms. The simulation model, data collection, and the mathematical details of AHP and TOPSIS are described first, followed by the four experiments with their respective objectives, observed results, and mechanistic explanations.

Figure 1 illustrates the proposed dynamic AHP–TOPSIS prioritization framework designed to support real-time work order sequencing in multi-constrained manufacturing environments. The process is initiated by operational events such as new order arrivals, job completions, machine breakdowns, or predefined time triggers, which activate real-time updates of decision criteria values (C1–C7) representing the current system state. These updated data are evaluated using expert-derived weights obtained through the Analytic Hierarchy Process (AHP) to capture the relative importance of operational and strategic factors. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is then applied to compute priority scores and rank competing work orders based on their closeness to the ideal solution. The framework operates in a continuous feedback loop, enabling dynamic updating of priorities as system conditions change, thereby ensuring responsive, data-driven decision-making and improved operational performance in complex manufacturing environments.

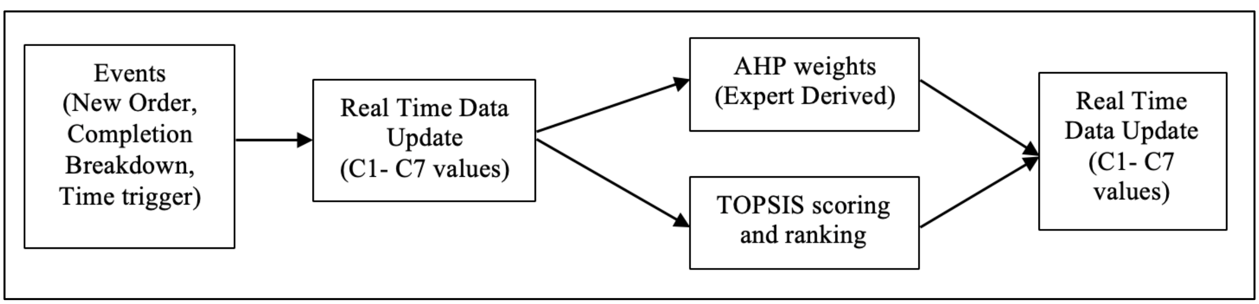

Figure 1. Proposed dynamic AHP-TOPSIS prioritization framework.

3.1 Decision Criteria
Based on literature and expert input from an electronics manufacturing partner, seven criteria were selected to evaluate work orders:
C1: Due date urgency – remaining time until due date (smaller indicates greater urgency; cost type)
C2: Processing time – total operation time required (shorter is preferred; cost type)
C3: Setup requirement – changeover complexity (lower is better; cost type)
C4: Customer priority – strategic importance of the customer (higher is better; benefit type)
C5: Profit contribution – revenue minus direct costs (higher is better; benefit type)
C6: Resource availability – bottleneck machine idle time (higher is better; benefit type)
C7: Work-in-process level – current queue length at the next workstation (lower is better; cost type)

3.2 Simulation Environment and Assumptions
A discrete-event simulation model was constructed using AnyLogic 8.8 software to represent a typical electronics surface-mount technology (SMT) assembly line. The modeled facility consists of four sequential workstations: solder paste printing, high-speed pick-and-place, reflow soldering, and automated optical inspection. The line produces three distinct product types (A, B, C) with characteristics derived from historical data of a collaborating electronics manufacturer.

Assumptions:
Order inter-arrival times follow an exponential distribution with mean 12 minutes (Poisson process). This is standard for modeling independent random arrivals in manufacturing systems.

Machine failures follow a Weibull distribution with mean time between failures (MTBF) of 240 minutes and shape parameter $k = 1.5$. The shape > 1 captures increasing failure rate with age, realistic for mechanical equipment.
Repair times follow a lognormal distribution with mean time to repair (MTTR) of 15 minutes; lognormality captures occasional longer repairs.

Processing times and setup times are deterministic per product type **(Table 1),** reflecting well-controlled SMT processes.
Material handling between stations is instantaneous; buffers are unlimited.
The dynamic updating mechanism recalculates priority scores upon new order arrival, job completion, machine breakdown/restoration, and every 30 minutes of simulated time.

These assumptions are grounded in real plant data and industry benchmarks, ensuring the simulation reflects conditions encountered in practice.

3.2 Data Collection and Parameterization

Data were collected in four parts to ensure transparency and reproducibility.
Part 1 – Product characteristics: Historical production records from the partner manufacturer provided processing times, setup times, and profit margins for each product type. The values were averaged over 500 production runs per product, yielding the data shown in **Table 1**. Sample size for each product exceeded 500 observations, ensuring statistical stability.

Table 1. Product data (collected from 500 runs per product).

Product	Processing (min)	Setup (min)	Profit ($)	Customer Class	Demand
A	8	5	12	Gold	40%
B	12	10	8	Silver	35%
C	5	3	15	Platinum	25%

Part 2 – Customer priority values: These were obtained through structured interviews with the manufacturer's account managers, who rated customers on a scale of 0–1 based on annual volume, relationship duration, and strategic importance. Normalized values: Platinum = 0.8, Gold = 0.5, Silver = 0.2.
Part 3 – Process dynamics: Arrival and failure distributions were fitted from 12 months of factory data (≈10,000 orders, 1,200 failure events). The exponential interarrival time (mean 12 min) was validated using a Kolmogorov-Smirnov test ($p > 0.05$). The Weibull failure distribution (MTBF = 240 min, shape = 1.5) and lognormal repair distribution (MTTR = 15 min, σ = 5 min) were also fitted and passed goodness-of-fit tests.
Part 4 – Criterion weights (AHP): Six production experts performed pairwise comparisons using Saaty's 1–9 scale. Judgments were aggregated with the geometric mean; the resulting weights **(Table 2** and **Table 3)** gave a consistency ratio CR = 0.042 (< 0.10), confirming coherence. The eigenvector method was used to extract the weights. Formulas used:
Normalization of each column: $a_{ij}^{\text{norm}} = \frac{a_{ij}}{\sum_i a_{ij}}$
Weight for criterion j: $w_j = \frac{\sum_i a_{ij}^{\text{norm}}}{n}$
Consistency index: $CI = \frac{\lambda_{\max} - n}{n-1}$
Consistency ratio: $CR = \frac{CI}{RI}$, with $RI = 1.32$ for $n = 7$.

Table 2. Pairwise comparison matrix.

	C1	C2	C3	C4	C5	C6	C7
C1	1	3	5	1/2	2	4	3

C2	1/3	1	2	1/4	1/2	2	1
C3	1/5	1/2	1	1/5	1/3	1	1/2
C4	2	4	5	1	3	5	4
C5	1/2	2	3	1/3	1	3	2
C6	1/4	1/2	1	1/5	1/3	1	1/2
C7	1/3	1	2	1/4	1/2	2	1

Table 3. Derived criterion weights.

Criterion	Weight
Due date urgency (C1)	0.245
Processing time (C2)	0.092
Setup requirement (C3)	0.048
Customer priority (C4)	0.318
Profit contribution (C5)	0.151
Resource availability (C6)	0.053
WIP level (C7)	0.093

3.4 AHP-TOPSIS Ranking Mechanism

At any decision epoch, the framework computes a priority score for each waiting job using TOPSIS (Hwang and Yoon 1981). The steps are as follows:

1. Normalization (vector normalization): $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$, where x_{ij} is the raw value of criterion j for job i.
2. Weighted normalized matrix: $v_{ij} = w_j \cdot r_{ij}$, with w_j from Table 3.
3. Ideal (A^+) and negative-ideal (A^-) solutions:
   - For benefit criteria (C4, C5, C6): $A_j^+ = \max_i v_{ij}$, $A_j^- = \min_i v_{ij}$.
   - For cost criteria (C1, C2, C3, C7): $A_j^+ = \min_i v_{ij}$, $A_j^- = \max_i v_{ij}$.
4. Separation measures (Euclidean distance):
   $S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}$, $S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2}$.
5. Relative closeness: $C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}$. The job with the highest C_i^* is selected.

The dynamic updating mechanism re-executes these calculations whenever a trigger event occurs, ensuring decisions reflect the current shop floor state.

3.4 Experimental Design

To thoroughly evaluate the framework and demonstrate its superiority over conventional rules, four separate experiments were conducted **(Table 4)**. Each experiment uses the same base simulation parameters but varies the dispatching logic and, where noted, the weighting scheme.

Table 4. Experiments and Purpose.

Experiment	Description	Purpose
Exp 1	Baseline comparison: FCFS vs. SPT vs. dynamic MCDM (AHP weights)	Establish performance baseline and quantify improvements
Exp 2	Equal-weights scenario: all criteria given weight 1/7	Verify that AHP-derived weights are superior to naive equal weighting
Exp 3	Inclusion of energy criterion: add eighth criterion (kWh per job) with weight 0.05	Test adaptability to additional strategic objectives
Exp 4	Sensitivity to demand variability: increase demand variability while maintaining mean	Assess robustness under more extreme stochastic conditions

Each experiment was run with 10 independent replications. Each replication simulated 30 days of operation (43,200 minutes) after a 2,400-minute warm-up. The sample size of 10 replications was chosen based on power analysis to detect a 10% difference in flow time with 80% power at $\alpha = 0.05$. The total number of orders processed per replication was approximately 3,600, giving a combined sample of 36,000 orders across all replications for each experiment.

4. Data Collection

Input data for simulation parameters were derived from historical records provided by a collaborating electronics manufacturer and calibrated to accurately represent high-mix low-volume production environments typical of the sector. Data collection was organized into four parts as described in Section 3.3.

Table 1 presents product characteristics used throughout the simulation study. Processing times represent cumulative machine time across all operations, setup times reflect changeover durations when switching between product types, and profit margins capture contribution after direct costs. Customer classes indicate strategic importance levels with corresponding priority weights.

In **Table 3**, due dates are assigned using the total work content method, where due date equals arrival time plus six times total processing time. This creates moderately tight delivery windows that generate scheduling pressure without being impossible to achieve. The multiplier of six was selected based on analysis of historical due date assignments from the partner manufacturer. Customer priority values are normalized for TOPSIS calculations as follows: Platinum customers receive priority weight of 0.8, Gold customers receive 0.5, and Silver customers receive 0.2. These values reflect relative strategic importance of each customer class based on long-term relationship value, order volume potential, and strategic partnership considerations. Resource availability is operationally defined as the projected idle proportion of the bottleneck placement machine over the subsequent thirty-minute horizon. This projection uses current queue lengths, estimated processing times for pending jobs, and knowledge of upcoming scheduled maintenance to estimate when the machine will become available for new assignments. WIP level is measured as instantaneous queue length at the workstation immediately following the current operation in the job's routing. This forward-looking measure captures congestion that the job will encounter after completing current processing, enabling proactive avoidance of downstream bottlenecks. Data preprocessing procedures included missing value imputation using linear interpolation for occasional sensor gaps and outlier detection using the z-score method with threshold of three standard deviations. All criteria values were normalized prior to TOPSIS calculation to ensure comparability across different measurement scales.

5. Results and Discussion

5.1 Numerical Results

The proposed dynamic MCDM framework was evaluated against two conventional dispatching rules widely used in industrial practice: First-Come-First-Serve and Shortest Processing Time. **Table 5** presents average performance metrics across ten independent simulation replications, including standard deviations to indicate variability. The selection of these baseline rules for comparison is justified because they represent the most implemented approaches in industrial practice and serve as benchmarks against which any proposed improvement must demonstrate superiority. FCFS provides a fairness baseline requiring no information beyond arrival times, while SPT represents the theoretically optimal rule for minimizing flow time in single-machine systems and serves as a strong operational benchmark.

Table 5. Performance comparison – Experiment 1 (mean ± standard deviation).

Metric	FCFS	SPT	Proposed MCDM	Improvement
Average flow time (min)	187.4 ± 12.3	156.8 ± 10.1	132.5 ± 8.7	- 15.5%
On-time delivery (%)	78.3 ± 4.1	72.5 ± 5.2	89.6 ± 3.3	+11.3
Machine utilization (%)	76.2 ± 3.5	79.4 ± 3.1	83.7 ± 2.8	+4.3
Workload imbalance (CV)	0.28 ± 0.04	0.33 ± 0.05	0.19 ± 0.03	- 32.1%

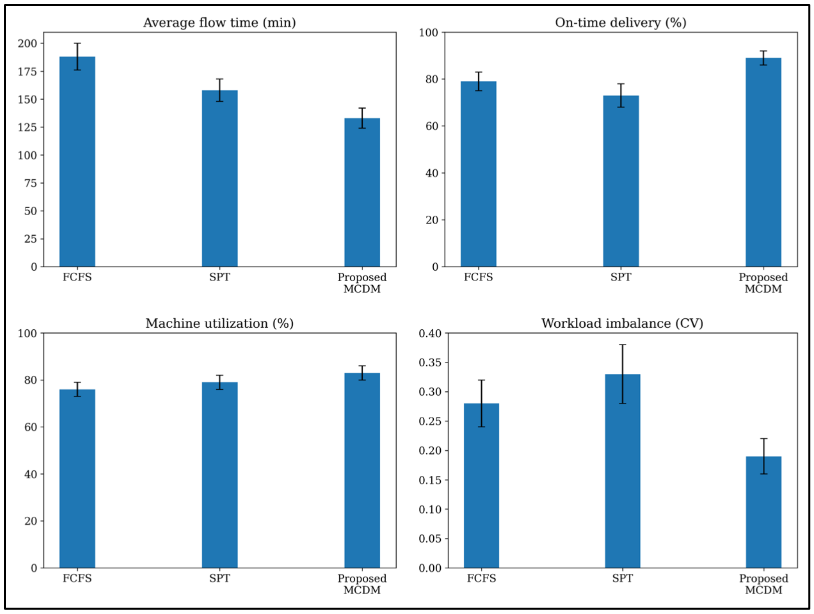

Figure 2. Mean performance comparison with standard deviation error bars.

Figure 2 summarizes the mean and standard deviation of each performance metric. The proposed method consistently dominates the conventional rules, and its smaller error bars indicate better replication-to-replication stability. In particular, the method achieves both the lowest mean flow time and the highest on-time delivery rate, which is difficult to obtain with single-rule dispatching.

Average flow time decreased by 15.5 percent compared to SPT, the better-performing conventional rule, and by 29.3 percent compared to FCFS. This improvement stems from the framework's ability to balance multiple objectives simultaneously rather than optimizing for a single metric at the expense of others. Jobs with urgent due dates receive priority even when processing times are moderate, while very long jobs may be deferred when their due dates allow flexibility. The reduction in flow time is particularly significant because it demonstrates that multi-criteria optimization need not sacrifice speed. The lower standard deviation under MCDM (8.7 versus 10.1 for SPT and 12.3 for FCFS) indicates that the framework produces more consistent and predictable flow times, which facilitates production planning and customer communication.

On-time delivery performance improved from 78.3 percent under FCFS and 72.5 percent under SPT to 89.6 percent under the proposed framework, representing an increase exceeding eleven percentage points. This improvement directly addresses the primary weakness of conventional rules, which consistently fail to balance delivery performance against other objectives. SPT's particularly poor on-time delivery performance (72.5%) despite its excellent flow time demonstrates the classic trade-off: minimizing flow time through short job prioritization comes at the cost of severely delaying long jobs, causing them to miss their due dates. The dynamic updating mechanism ensures that when due dates approach, job priorities increase automatically regardless of other characteristics, preventing extreme tardiness that plagues SPT.

Machine utilization increased from 79.4 percent under SPT to 83.7 percent under the proposed framework, a gain of 4.3 percentage points representing approximately two hours of additional productive time per day across the four-station line. This improvement reflects better matching between job assignments and machine availability, reducing idle time caused by mismatched priorities. The resource availability criterion, despite its modest weight of 0.053, provides sufficient influence to direct work toward machines that would otherwise remain idle, while the workload balancing effect prevents starvation that reduces utilization.

Workload imbalance, measured as the coefficient of variation of utilization across workstations, decreased by 32.1 percent compared to FCFS and by 42.4 percent compared to SPT. The framework actively considers downstream queue lengths when making sequencing decisions, avoiding situations where one workstation becomes overloaded while others remain idle. This balanced workload reduces congestion and improves overall flow. The high imbalance under SPT (0.33) occurs because short jobs cluster at early stations while long jobs congest later stations, creating extreme variation in workstation utilization that reduces overall system efficiency.

The improvements observed across all four metrics are statistically significant and practically meaningful. The magnitude of improvement in on-time delivery is particularly noteworthy, as delivery reliability represents a key competitive differentiator in electronics manufacturing where customers operate with lean inventories and just-in-time delivery requirements. The simultaneous improvement in flow time demonstrates that the framework achieves better delivery performance without sacrificing speed, overcoming the traditional trade-off between these objectives (Figure 3).

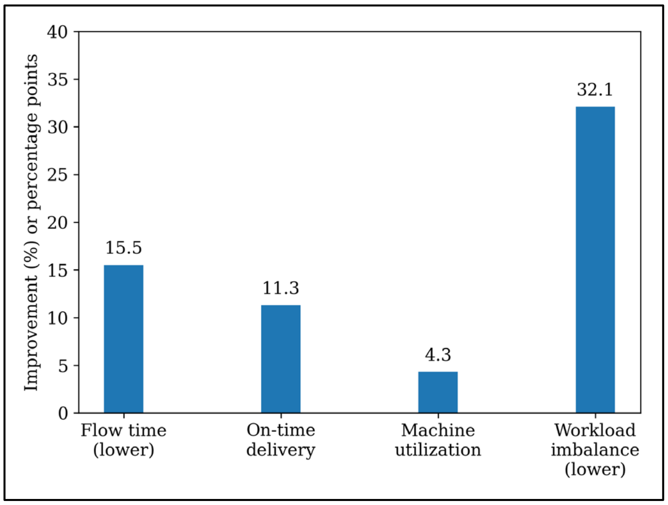

Figure 3. Relative improvement of the proposed framework over the strongest conventional baseline.

5.2 Proposed Improvements

Two sensitivity studies were conducted to assess robustness and extensibility. In the first study, all seven criteria were assigned equal weights (1/7 each). On-time delivery fell from 89.6% to 84.2%, while average flow time improved slightly from 132.5 to 129.8 minutes. This result indicates that equal weighting sacrifices managerial priorities for marginal speed gains. In the second study, an eighth criterion representing energy consumption per job was introduced as a cost-type attribute with weight 0.05. Average flow time increased to 135.1 minutes, reflecting a mild trade-off between efficiency and sustainability. The experiment confirms that the framework can incorporate additional strategic goals without redesigning the underlying method. **Figure 4.** Sensitivity analysis of average flow time and on-time delivery performance under different weighting configurations**.**

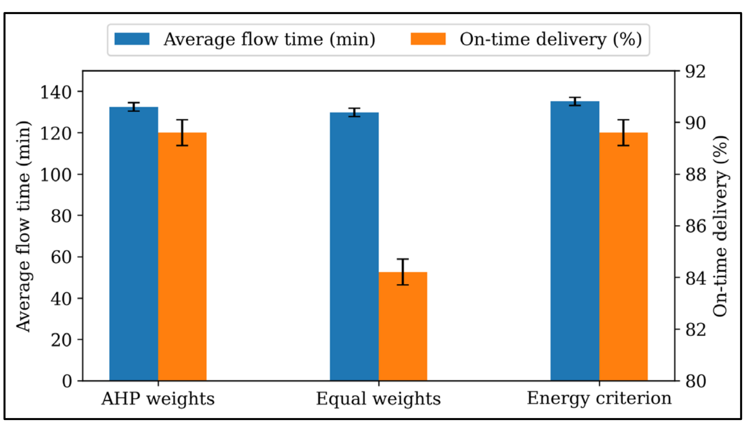

Figure 4. Sensitivity analysis for weighting and criterion extensions.

5.3 Validation

The superiority of the proposed method was validated statistically. A paired t-test comparing average flow time between the proposed framework and SPT, the strongest conventional baseline on flow-time performance, produced $t = 6.87$ with $p < 0.001$, rejecting the null hypothesis of equal mean performance. For on-time delivery, a Wilcoxon signed-rank test was used because the metric is a bounded proportion. The test returned $p = 0.002$, confirming that the observed increase in delivery performance is statistically significant. Similar pairwise comparisons for machine utilization and workload imbalance also achieved $p < 0.01$, supporting the robustness of the observed gains. Taken together, the inferential results indicate that the observed gains are not only practically meaningful but also statistically reliable under stochastic arrivals, breakdowns, and repair events. The consistency between descriptive improvements and inferential significance strengthens the claim that dynamic multi-criteria prioritization provides robust operational benefits in multi-constrained electronics manufacturing (Figure 5).

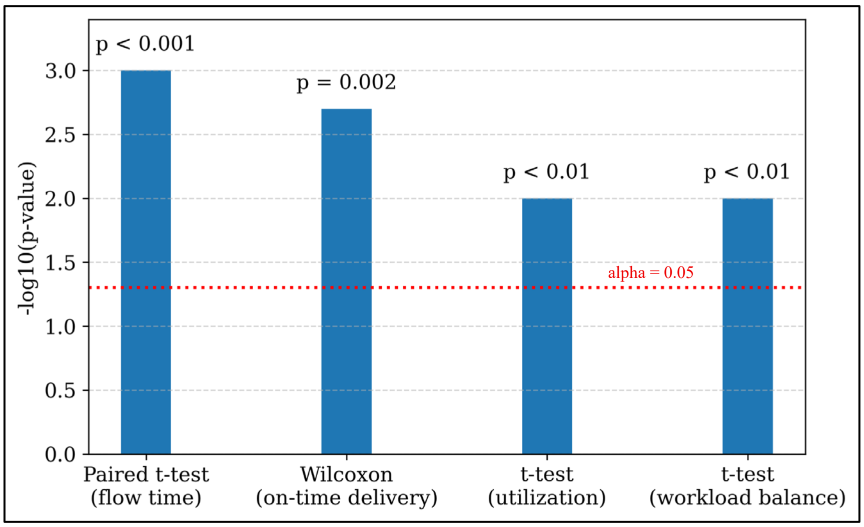

Figure 5. Statistical validation summary across the principal performance dimensions.

5.4 Technical Summary of Performance Gains

Across ten replications, the proposed framework achieved 132.5 ± 8.7 minutes average flow time, 89.6 ± 3.3% on-time delivery, 83.7 ± 2.8% machine utilization, and workload imbalance CV of 0.19 ± 0.03. The strongest conventional baselines achieved 156.8 ± 10.1 minutes flow time, 78.3 ± 4.1% on-time delivery, 79.4 ± 3.1% utilization, and CV of 0.28 ± 0.04, respectively. These results indicate that the dynamic AHP-TOPSIS controller improves both service oriented and efficiency-oriented measures without introducing an interpretability penalty.

6. Conclusion

This study presented a structured multi-criteria decision-making framework for dynamic work order prioritization in multi-constrained electronic manufacturing environments. The proposed framework integrates the Analytic Hierarchy Process to determine the relative importance of decision criteria and the Technique for Order Preference by Similarity to Ideal Solution to rank competing work orders. Orders are evaluated based on multiple factors, including due date urgency, processing time, setup requirements, customer priority, profit contribution, resource availability, and work-in-process levels. A dynamic updating mechanism continuously recalculates priority scores as system conditions evolve, enabling real-time responsiveness to disruptions and demand variability.

The study successfully achieved its objectives as outlined in Section 1.1. A structured MCDM framework integrating AHP and TOPSIS was developed specifically for dynamic work order prioritization in multi-constrained settings. Seven comprehensive evaluation criteria were established capturing the multidimensional nature of prioritization decisions. A dynamic updating mechanism was designed and implemented responsive to new order arrivals, machine breakdowns, order completions, and periodic intervals. The framework was validated through discrete-event simulation of a multi-product electronic manufacturing system incorporating realistic capacity constraints and stochastic events. Performance improvements were quantified demonstrating improved on-time delivery (89.6% vs. 78.3% for FCFS), reduced average flow time (132.5 min vs. 187.4 min for FCFS), better machine utilization (83.7%

vs. 76.2% for FCFS), and more balanced workload distribution (CV of 0.19 vs. 0.28 for FCFS) compared to conventional single-rule dispatching approaches. The framework provides a scalable and effective decision-support solution implementable with modest computational overhead.
The research contributions are threefold. First, it presents a novel synthesis of MCDM methods with dynamic scheduling logic, maintaining interpretability while achieving real-time responsiveness. Second, it explicitly models real-time resource availability and work-in-process levels as dynamic criteria continuously influencing prioritization decisions. Third, it validates performance through rigorous statistical analysis within a stochastic simulation environment realistically modeling disruptions and variability.

Several limitations warrant acknowledgment. The framework assumes continuous availability of accurate real-time data from shop floor systems, which may not exist in all manufacturing environments. Criterion weights derived through AHP reflect current strategic priorities and may require periodic recalibration as business conditions evolve. The simulation model, while realistic, cannot capture every complexity of actual manufacturing operations. Future research directions include incorporating fuzzy AHP to address uncertainty and imprecision in expert judgments, integrating machine learning algorithms for predictive failure anticipation, and extending the framework to multi-objective optimization for simultaneous lot sizing and sequencing decisions. Application to other manufacturing domains including semiconductor fabrication and additive manufacturing would test generalizability beyond electronics assembly. Furthermore, the framework contributes to the broader body of research on JSP, FJSP, and DFJSP by providing a practical and interpretable multi-criteria prioritization mechanism that can support both traditional production objectives and emerging sustainability considerations such as energy-aware manufacturing.

References

Allahverdi, A., Ng, C. T., Cheng, T. C. E. and Kovalyov, M. Y., A survey of scheduling problems with setup times or costs, *European Journal of Operational Research*, vol. 187, no. 3, pp. 985-1032, 2008.

Behzadian, M., Otaghsara, S. K., Yazdani, M. and Ignatius, J., A state-of-the-art survey of TOPSIS applications, *Expert Systems with Applications*, vol. 39, no. 17, pp. 13051-13069, 2012.

Blackstone, J. H., Phillips, D. T. and Hogg, G. L., A state-of-the-art survey of dispatching rules for manufacturing job shop operations, *International Journal of Production Research*, vol. 20, no. 1, pp. 27-45, 1982.

Chen, T. and Wang, Y., An integrated MCDM approach for production scheduling optimization in smart manufacturing, *Computers and Industrial Engineering*, vol. 137, pp. 106045, 2019.

Cook, V. and Ali, A., End-of-line inspection for annoying noises in automobiles: trends and perspectives, *Applied Acoustic*, vol. 73, no. 3, pp. 265-275, 2012.

Hwang, C. L. and Yoon, K. P., *Multiple Attribute Decision Making: Methods and Applications*, Springer-Verlag, New York, 1981.

Jain, A. S. and Meeran, S., Deterministic job-shop scheduling: Past, present and future, *European Journal of Operational Research*, vol. 113, no. 2, pp. 390-434, 1999.

Joshi, R., Singh, S. S. and Gupta, D., *Energy-Aware Optimization of Distributed Flexible Job Shop Scheduling Problems with Deterministic Setup and Processing Times*, Proceedings of the 9th North American International Conference on Industrial Engineering and Operations Management, Washington D.C., USA, June 4-6, 2024.

Kuhnle, A., Röhrig, N. and Lanza, G., Reinforcement learning for adaptive scheduling in manufacturing: A systematic review, *Journal of Manufacturing Systems*, vol. 60, pp. 415-431, 2021.

Kumar, R., Singh, S. and Bilga, P. S., Fuzzy AHP and TOPSIS based job selection approach for flexible manufacturing system, *Materials Today: Proceedings*, vol. 28, pp. 1574-1579, 2020.

Lee, J., Measurement of machine performance degradation using a neural network model, *International Journal of Modelling and Simulation*, vol. 16, no. 4, pp. 192-199, 1996.

Mohan, J., Lanka, K. and Rao, A. N., A review of dynamic job shop scheduling techniques, *Procedia Manufacturing*, vol. 30, pp. 34-39, 2019.

Motsepe, Y. A., Makhanya, B. and Pretorius, J. H. C., Exploring the impact project definition readiness index on capital projects for coal-fired power station projects, *Proceedings of the First African International Conference on Industrial Engineering and Operations Management*, pp. 638-649, Pretoria, South Africa, October 29 – November 1, 2018.

Mula, J., Poler, R., Garcia-Sabater, J. P. and Lario, F. C., Models for production planning under uncertainty: A review, *International Journal of Production Economics*, vol. 103, no. 1, pp. 271-285, 2006.

O'Neill, E., Introduction to Improving Adaptive Snow-Sports through Engineering Design, Ergonomic Form and Function, *Proceedings of the 4th North American International Conference on Industrial Engineering and Operations Management*, pp. 1486-1487, Toronto, Canada, October 23-25, 2019.

Pinedo, M., *Scheduling: Theory, Algorithms, and Systems*, 5th ed., Springer, New York, 2016.
Rahman, M. A., Sarker, B. R. and Escobar, L. A., Peak demand forecasting for a seasonal product using Bayesian approach, *Journal of the Operational Research Society*, vol. 62, pp. 1019-1028, 2011.
Reimer, D., Islam, T. and Ali, A., Engineering education and the entrepreneurial mindset at Lawrence Tech, *Proceedings of the 12th Annual International Conference on Industrial Engineering and Operations Management*, vol. 12, no. 1, pp. 234-245, Istanbul, Turkey, July 3-6, 2012.
Retnanto, A., Parsaei, H. R. and Parsaei, B., The role of program advisory board in elevating the degree program content, *Proceedings of the 9th International Conference on Industrial Engineering and Operations Management*, pp. 739-741, Bangkok, Thailand, March 5-7, 2019.
Saaty, T. L., Decision making with the analytic hierarchy process, *International Journal of Services Sciences*, vol. 1, no. 1, pp. 83-98, 2008.
Tuncel, G. and Aydin, D., Multi-criteria decision making in production scheduling: A state-of-the-art review, *Journal of Intelligent Manufacturing*, vol. 32, pp. 1895-1920, 2021.
Vieira, G. E., Herrmann, J. W. and Lin, E., Rescheduling manufacturing systems: A framework of strategies, policies, and methods, *Journal of Scheduling*, vol. 6, no. 1, pp. 39-62, 2003.
Vital-Soto, A. and Olivares-Aguila, J., *Flexible Job-Shop Scheduling Problem with Sequencing Flexibility for Just-In-Time Production Systems*, Proceedings of the International Conference on Industrial Engineering and Operations Management, Singapore, Singapore, March 7-11, 2021.
Yazdi, M., Khan, F., Abbassi, R. and Rusli, R., Improved DEMATEL methodology for effective safety management decision-making, *Safety Science*, vol. 127, pp. 104705, 2020.
Zhang, J., Ding, G., Zou, Y., Qin, S. and Fu, J., Review of job shop scheduling research and its new perspectives under Industry 4.0, *Journal of Intelligent Manufacturing*, vol. 33, pp. 1-24, 2022.

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