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Mathematical Optimization of Batch Size and Changeover Scheduling for Manufacturing Productivity Enhancement in Multi-Product Production Systems

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Research Article

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Abstract

Frequent machine changeovers and inefficient batch sizing significantly reduce operational efficiency in multi-product manufacturing systems. This research introduces an integrated mathematical optimization framework for minimizing setup losses, improving machine utilization, and increasing production throughput through optimized batch scheduling and changeover sequencing. The proposed methodology combines mixed-integer linear programming (MILP), queueing analysis, and Overall Equipment Effectiveness (OEE) modeling to determine optimal production batch sizes and machine scheduling configurations. The framework incorporates demand variability, processing time distributions, setup dependencies, inventory constraints, and production sequencing rules to generate optimal operational schedules for high-mix manufacturing environments. Simulation-based validation will be performed using real manufacturing operational datasets to compare optimized scheduling policies against conventional fixed-batch production systems. Key performance metrics will include machine idle time, production yield, setup frequency, throughput rate, cycle time, and manufacturing cost efficiency. The study aims to provide a data-oriented manufacturing optimization strategy applicable to automotive, medical device, and industrial equipment manufacturing operations where production flexibility and operational efficiency are critical.

Keywords

Mixed-integer linear programming (MILP); Production scheduling optimization; Batch size mathematical modeling; Changeover reduction analytics; Overall Equipment Effectiveness (OEE) modeling; Lean manufacturing systems; Queueing theory in production operations; Multi-product manufacturing optimization; Discrete manufacturing analytics; Industrial engineering productivity modeling.

I. Introduction

Manufacturing systems are increasingly characterized by high product variety, demand volatility, and the need for improved efficiency with operational flexibility. In multi-product environments, production scheduling and batch sizing significantly influence setup time, machine utilization, inventory levels, and overall performance. Poor coordination among these decisions leads to excessive changeovers, higher idle time, increased work-in-process (WIP), and reduced Overall Equipment Effectiveness (OEE).

A. Background and Motivation

Multi-product manufacturing systems involve shared-resource constraints where sequence-dependent setups and demand uncertainty create complex scheduling challenges. Batch sizing represents a trade-off between setup frequency and inventory cost, affecting responsiveness and efficiency. Recent advances in MILP, queueing theory, and Industry 4.0 data enable more integrated and data-driven optimization approaches.

B. Problem Statement

Existing studies often treat batch sizing, scheduling, and changeover optimization as separate problems, limiting their ability to capture real system interdependencies. Many models focus only on makespan or setup reduction, while ignoring key performance metrics such as throughput, cycle time, WIP, and OEE. In addition, deterministic assumptions reduce applicability in stochastic high-mix manufacturing environments.

C. Proposed Solution

To address these limitations, this study develops an integrated optimization framework that jointly optimizes batch sizing, machine assignment, production sequencing, and changeover

scheduling using a Mixed-Integer Linear Programming (MILP) model. The proposed framework is further enhanced through queueing theory for capturing production congestion and flow dynamics, OEE modeling for comprehensive productivity evaluation, and discrete-event simulation for performance validation under stochastic demand conditions. This hybrid modeling approach enables both optimal decision-making and realistic system-level performance assessment in complex manufacturing environments.

D. Contributions

The main contributions of this study include the development of a unified MILP-based framework that integrates batch sizing and production scheduling within a single optimization structure. The study further incorporates queueing theory to model system congestion, waiting behavior, and production flow dynamics, enabling a more realistic representation of manufacturing performance. In addition, Overall Equipment Effectiveness (OEE) is integrated to provide a holistic measure of productivity by capturing availability, performance, and quality simultaneously. Finally, the proposed framework is validated through discrete-event simulation under stochastic demand scenarios to ensure robustness and practical applicability. Collectively, these contributions establish a scalable and data-driven decision-support system for improving operational efficiency in high-mix, multi-product manufacturing environments.

II. Literature Review

Manufacturing productivity optimization has increasingly relied on mathematical programming and data-driven decision models, particularly in multi-product environments where scheduling complexity, sequence-dependent setups, and demand uncertainty significantly impact system performance. Recent research indicates that integrating MILP, metaheuristics, and analytics-based approaches can significantly improve throughput, resource utilization, and operational efficiency while reducing non-value-added activities.

A. Production Scheduling Optimization

Production scheduling is a combinatorial decision problem influenced by capacity constraints, demand variability, and sequence-dependent setup times. Traditional rule-based approaches are often insufficient to handle such complexity effectively. In contrast, MILP and metaheuristic-based optimization methods have demonstrated superior performance in

minimizing makespan and improving resource utilization in complex manufacturing systems [1], [2], [3], [4].

B. Batch Size and Lot-Sizing Optimization

Batch sizing plays a critical role in balancing setup costs, inventory holding costs, and system responsiveness. Prior studies show that integrated lot-sizing and scheduling models outperform decoupled approaches, particularly under demand uncertainty. Additionally, dynamic batch sizing strategies improve flexibility and responsiveness in high-mix manufacturing environments [5], [6].

C. Changeover Scheduling and Sequence Optimization

Sequence-dependent setup times are a major source of inefficiency in multi-product manufacturing systems. Research demonstrates that MILP-based sequencing models can significantly reduce changeover time and improve production continuity. Effective setup-aware scheduling is therefore essential for minimizing idle time and improving flow efficiency in production systems [7], [8], [9], [10], [11].

D. Lean Manufacturing and Productivity Metrics

Lean manufacturing and Quick Response Manufacturing (QRM) emphasize waste reduction and continuous improvement in operational efficiency. A consistent finding in the literature is that reducing setup time has a direct and significant impact on overall productivity. In this context, Overall Equipment Effectiveness (OEE) is widely adopted as a composite performance metric integrating availability, performance, and quality dimensions into a single indicator [12], [13], [14].

E. Industry 4.0 and Data-Driven Optimization

Industry 4.0 technologies have transformed manufacturing systems through real-time monitoring, predictive analytics, and intelligent decision-making capabilities. Data-driven scheduling models enhance adaptability and decision accuracy in dynamic environments, while AI and IIoT technologies improve bottleneck detection, operational transparency, and adaptive control mechanisms [15], [16], [17], [18], [19].

F. Research Gaps and Future Directions

Despite extensive advancements, most existing studies continue to treat batch sizing, scheduling, and changeover optimization as isolated problems, limiting their ability to capture system-level interactions in manufacturing environments. Furthermore, many models focus narrowly on makespan or setup reduction, while overlooking broader performance measures such as throughput, cycle time, WIP, and OEE. Another key limitation is the widespread use of deterministic assumptions, which reduces model applicability in real-world stochastic manufacturing systems. Additionally, there remains a lack of integrated frameworks combining MILP, queueing theory, and simulation-based validation, which is essential for capturing realistic production dynamics. Future research should therefore focus on unified stochastic optimization frameworks that integrate batch sizing, sequencing, and changeover decisions. The combination of MILP with simulation, AI-driven forecasting, digital twins, and Industry 4.0 technologies such as IIoT will significantly enhance system adaptability, robustness, and real-time decision-making capability. Incorporating sustainability and energy-aware metrics will further increase industrial and academic relevance.

III. METHODOLOGY

The proposed study develops a unified MILP-based optimization framework for joint batch sizing and sequence-dependent changeover scheduling in multi-product manufacturing systems. The framework integrates Mixed-Integer Linear Programming, queueing analysis, Overall Equipment Effectiveness (OEE) evaluation, and discrete-event simulation to minimize non-value-added time, reduce idle losses, and improve throughput under stochastic demand and sequence-dependent setup conditions. The methodology follows an end-to-end decision-support pipeline from data acquisition to validation.

A. Integrated Manufacturing Optimization Framework and Dataset Description

The proposed framework integrates production planning, optimization, performance evaluation, and simulation validation into a unified decision-support system. The workflow begins with data acquisition from ERP, MES, machine logs, inventory systems, production planning databases, and quality records. After preprocessing, a sequence-dependent setup matrix is generated and incorporated into the MILP-based scheduling and batch optimization model. The optimized schedules are subsequently evaluated using queueing theory and OEE

analysis to assess system utilization, congestion, and productivity performance. Finally, discrete-event simulation and statistical analysis are employed to validate model robustness.

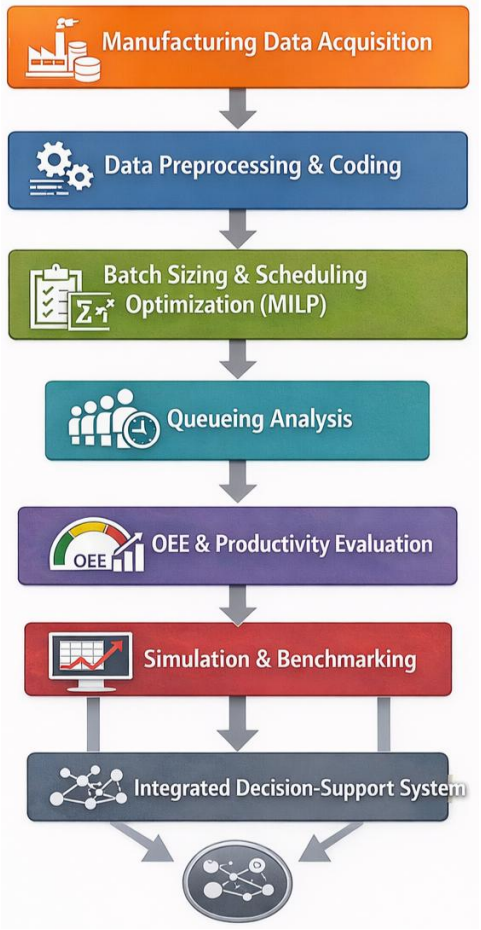

Fig. 1 Overall Research Framework of the Proposed Manufacturing Optimization System

The framework illustrates a sequential methodology that begins with manufacturing data acquisition and preprocessing, followed by MILP-based batch sizing and scheduling optimization, queueing analysis, and OEE evaluation. The optimized results are validated through simulation and benchmarking, supporting decision-making through an integrated decision-support system.

The dataset represents a high-mix manufacturing environment spanning 12 months and includes 20-50 products, 5-15 machines, and weekly scheduling cycles. Key variables include demand, processing time, setup time, machine capacity, inventory levels, yield rates, and downtime.

B. Data Management and Preprocessing

The data management and preprocessing stage transforms raw manufacturing data into a structured and optimization-compatible format. This stage ensures data consistency, improves model reliability, and enables accurate downstream optimization and performance evaluation. Raw data obtained from ERP, MES, machine logs, inventory systems, and production databases are systematically processed to ensure completeness and consistency. Missing values are treated using mean or median imputation depending on the statistical distribution of each variable. Duplicate records are removed to eliminate redundancy and improve dataset integrity. Outlier detection is performed using the Z-score method:

$$Z = \frac{x - \mu}{\sigma}$$

where x represents the observed value, μ denotes the mean, and σ is the standard deviation. Observations are classified as outliers when:

$$| Z |> 3$$

Values exceeding this threshold are considered statistically anomalous and are either removed or adjusted depending on data reliability.

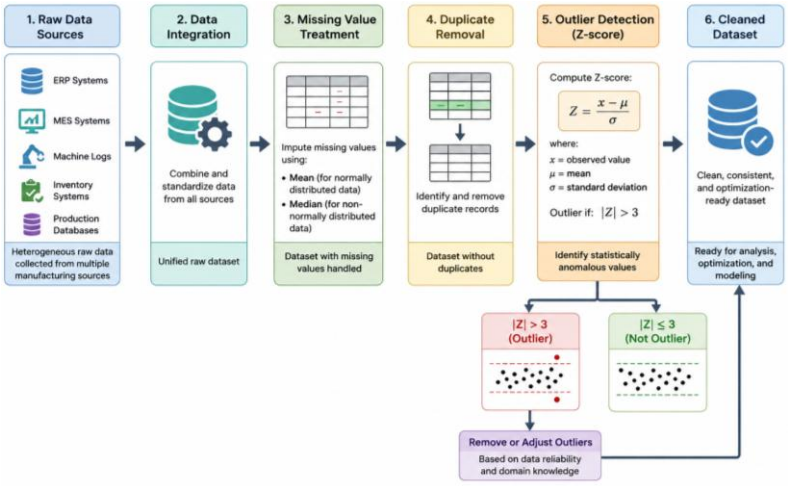

Fig. 2 Data Cleaning Workflow

After preprocessing, products are encoded using unique identifiers along with machine assignments, product family classifications, and setup categories. A sequence-dependent setup matrix S_{ij} is constructed to capture transition times between product pairs, forming the basis for changeover optimization. Demand normalization is applied to improve numerical stability and ensure comparability across products:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This transformation scales demand values between 0 and 1, improving convergence behavior in the optimization model.

Table. I *Product Coding and Setup Matrix Structure*

Product ID	Product Family	Machine Assignment	Setup Category	Demand (Normalized)	Setup Time (S_ij)
P1	F1	M1	A	0.65	S12
P2	F1	M2	A	0.72	S21
P3	F2	M1	B	0.40	S13
P4	F3	M3	C	0.85	S24
P5	F2	M2	B	0.55	S32

The overall data pipeline follows a sequential architecture ensuring smooth integration between data acquisition, optimization modeling, and performance evaluation stages.

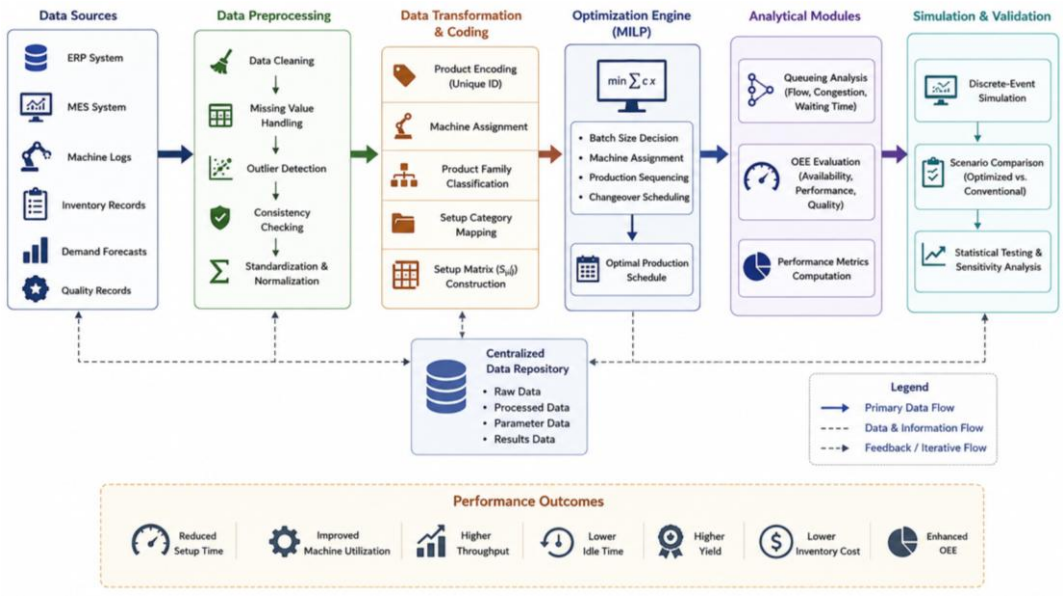

Fig. 3 Data Flow Architecture

C. Mixed-Integer Linear Programming (MILP) Optimization Model

The core of the proposed framework is formulated as a Mixed-Integer Linear Programming (MILP) model that simultaneously optimizes batch sizing, machine assignment, production sequencing, and changeover scheduling in a multi-product manufacturing environment.

The decision variables are defined as:

- B_p : batch size of product p
- X_{pmt} : assignment of product to machine

- Y_{ijt} : sequence-dependent setup decision

The objective function minimizes total non-value-added operational cost while maximizing production efficiency:

$$\min Z = \sum ST_{ij} Y_{ijt} + w_2 \sum Idle_{mt} + w_3 \sum InventoryCost_p - w_4 \sum Throughput_p$$

where w_1, w_2, w_4 are weighting coefficients representing the relative importance of each component.

The optimization model is subject to the following operational constraints:

1) Demand Satisfaction Constraint

$$\sum Q_{pmt} \geq D_p$$

Ensures that production meets or exceeds demand for each product over the planning horizon.

2) Machine Capacity Constraint

$$\sum PT_p \, X_{pmt} + \sum ST_{ij} \, Y_{ijt} \leq MC_m$$

Guarantees that total processing and setup times do not exceed available machine capacity.

3) Inventory Balance Constraint

$$INV_t = INV_{t-1} + Production_t - Demand_t$$

This constraint maintains inventory continuity by accounting for inventory carried over from the previous period, newly produced units, and customer demand.

4) Batch Size Constraint

$$B_{min} \leq B_P \leq B_{max}$$

This constraint restricts batch sizes within predefined operational limits to avoid excessively small or excessively large production lots.

5) Binary Assignment Constraint

$$Y_{ijt} \in \{0,1\}$$

This binary constraint determines whether a setup transition between product *i* and product *j* occurs. A value of 1 indicates that the transition takes place, while 0 indicates otherwise.

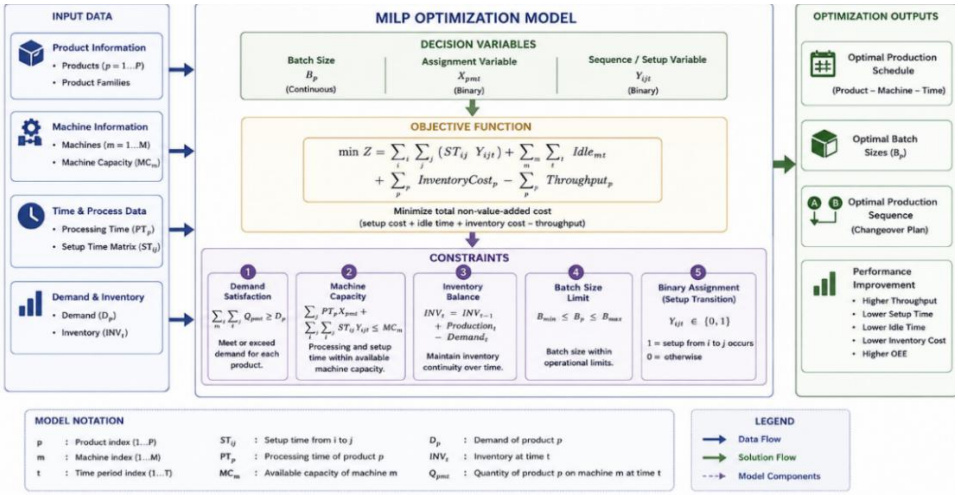

Fig. 4 MILP Optimization Structure

The model integrates demand, capacity, processing time, setup dependencies, and inventory dynamics to generate an optimal production schedule minimizing non-value-added activities.

D. Performance Evaluation, Validation, and Sensitivity Analysis Framework

To evaluate optimization effectiveness, queueing theory, Overall Equipment Effectiveness (OEE) analysis, discrete-event simulation, and statistical validation are integrated into a unified performance assessment framework. The production system is modeled as an M/M/c queue, where c represents the number of parallel machines in the system. This formulation is more appropriate for multi-machine, high-mix manufacturing environments. The utilization factor is defined as:

$$\rho = \frac{\lambda}{c\mu}$$

where λ represents the average arrival rate and μ denotes the average service rate. The utilization factor indicates the proportion of system capacity being used and serves as a key measure of operational efficiency. The expected number of jobs waiting in the queue is determined by:

$$L_q = \frac{(\lambda/\mu)^C . P}{c!\,(1-\rho)^2} \; . P_0$$

Where, L_q represents the average queue length and P_0 is the probability that no jobs are in the system. This metric quantifies congestion within the production system and reflects work-in-process accumulation under multi-server conditions. The average waiting time in the queue is expressed as:

$$W_p = \frac{L_q}{\lambda}$$

Where, W_p denotes the expected waiting time in the queue. Lower values indicate smoother production flow and reduced delays. while the total time in the system is:

$$W = W_q + \frac{1}{\mu}$$

Lower values of these measures indicate smoother production flow, reduced congestion, and improved system responsiveness.

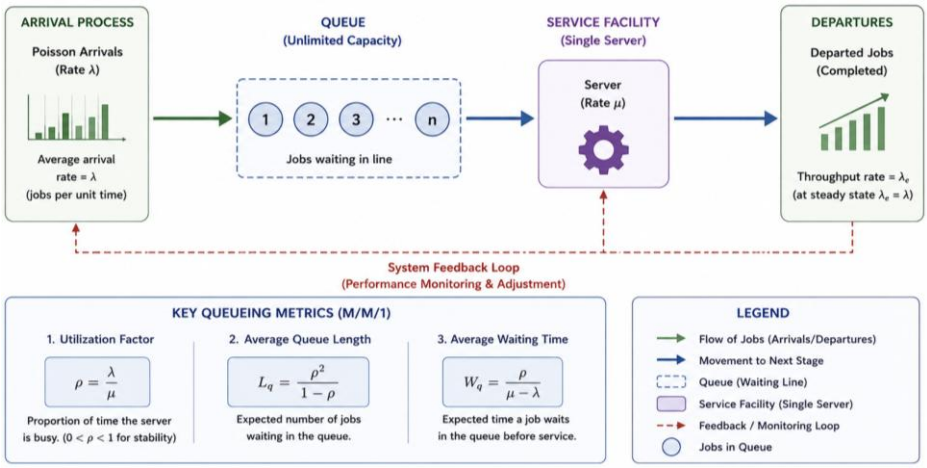

Fig. 5 Queueing System Model

To evaluate manufacturing productivity, Overall Equipment Effectiveness (OEE) is employed as a comprehensive performance indicator combining availability, performance, and quality. Availability is calculated as:

$$Availability = \frac{Operating\ Time}{Planned\ Production\ Time}$$

Where, *Operating Time* represents actual productive machine time and *Planned Production Time* denotes the scheduled operating period. This measure reflects the impact of breakdowns, setups, and downtime on production availability. Performance efficiency is computed as:

$$Performance = \frac{Ideal\ Cycle\ Time \times Total\ Output}{Operating\ Time}$$

This metric evaluates how closely actual production speed approaches the ideal manufacturing rate. Quality performance is determined using:

$$Quality = \frac{Good\ Units}{Total\ Units}$$

Where, *Good Units* represent defect-free products and *Total Units* denote total production output. This measure captures the effect of quality losses on manufacturing effectiveness. The overall OEE value is then calculated as:

$$OEE = Availability \times Performance \times Quality$$

This composite indicator provides a holistic assessment of equipment productivity by simultaneously considering downtime losses, speed losses, and quality losses.

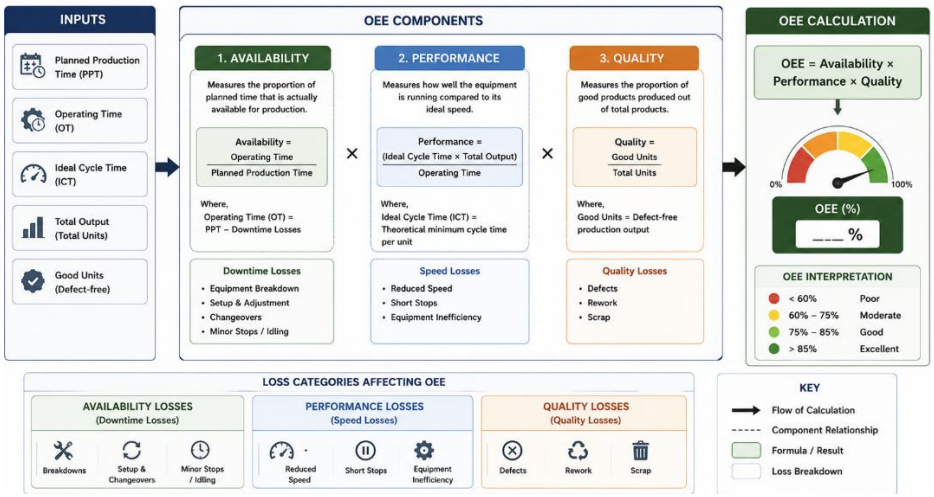

Fig. 6 OEE Evaluation Framework

Fig.6 presents the hierarchical structure of OEE and the interaction among availability, performance, and quality components.

For validation, a discrete-event simulation is conducted to compare a baseline fixed-batch production system with the proposed MILP-optimized system. The simulation spans 12 months with 30 independent replications. Demand uncertainty is modeled at ±10%, ±20%, and ±30%, while the manufacturing system includes 20–50 products processed on 5–15 machines.

Table. II *Simulation Configuration*

Parameter	Description	Value
Planning Horizon	Simulation duration	12 Months
Replications	Number of runs	30
Demand Variability	Uncertainty levels	±10%, ±20%, ±30%
Product Range	Number of products	20–50
Machine Range	Number of machines	5–15
System Type	Manufacturing environment	Multi-product, high-mix
Scheduling Policy	Baseline vs Optimized	Fixed batch vs MILP

The performance improvements generated by the optimization model are quantified through statistical analysis. Percentage improvement over the baseline system is calculated as:

$$Improvement\ (\%) = \frac{Optimized - Baseline}{Baseline} \times 100$$

This metric measures the relative gain achieved by the optimized production strategy compared with conventional scheduling practices. To evaluate statistical significance, a paired t-test is performed using:

$$t = \frac{\bar{d}}{s_d\ \sqrt{n}}$$

Where, $\bar{d}$ is the mean difference between paired observations, $s_d$is the standard deviation of the differences, and nnn is the number of paired samples. Model validation further includes feasibility checking, solver convergence analysis, and sensitivity testing under different demand scenarios.

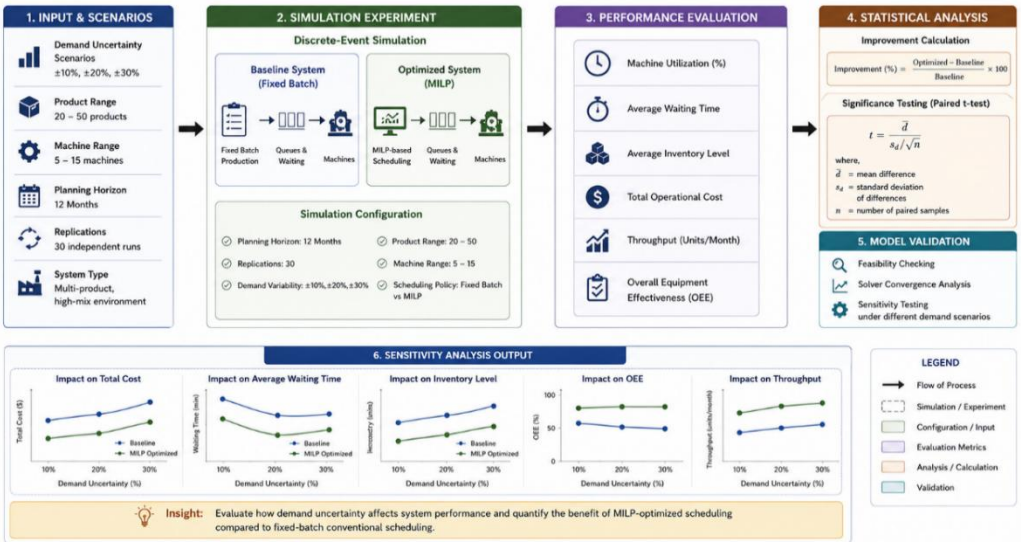

Fig. 7 Sensitivity Analysis Framework

Fig.7 illustrates the sensitivity analysis process used to evaluate model performance under different demand uncertainty scenarios.

System performance is evaluated using throughput rate, machine utilization, setup frequency, idle time, cycle time, inventory cost, production yield, and OEE.

Table. III *KPI Definitions and Mathematical Formulas*

KPI	Definition	Mathematical Expression
Throughput	Output per unit time	$Throughput\ = \frac{Total\ Output}{Time}$
Machine Utilization	Machine usage efficiency	$Utilization\ = \frac{Busy\ Time}{Total\ Available\ Time}$

Setup Frequency	Number of changeovers	$Count\ of\ Y_{ijt}\ transitions$
Idle Time	Non-productive machine time	$Idle\ Time\ =\ Available\ Tim - Operating\ Time$
Cycle Time	Time per unit production	$Cycle\ Time\ = \frac{Total\ Processing\ Time}{Units}$
Inventory Cost	Holding cost of stock	$IC = h \sum_t INV_t$
Production Yield	Quality efficiency	$Yield\ = \frac{Good\ Units}{Total\ Units}$
OEE	Overall equipment effectiveness	$OEE\ =\ Availability\ \times\ Performance\ \times\ Quality$

This table provides formal definitions and mathematical expressions for all performance indicators used in the evaluation framework. Unlike traditional decoupled approaches, this model jointly optimizes batch sizing, sequencing, and machine allocation within a single MILP formulation.

IV. Results and Discussion

The proposed MILP-based optimization framework was evaluated using a 12-month simulation dataset and compared against a fixed-batch baseline system. Results demonstrate significant improvements across all key performance indicators.

A. Results

The MILP-based optimization model successfully generated feasible and high-quality production schedules by jointly optimizing batch sizes, machine assignments, and sequence-dependent changeover decisions while satisfying all demand and capacity constraints. Compared with the baseline scheduling strategy, the proposed framework achieved notable improvements across all evaluated performance metrics.

Table. IV *Baseline vs Optimized Manufacturing Performance Comparison*

Metric	Baseline	Optimized	Improvement (%)
Throughput (Units/Day)	1,120	1,342	19.8
Machine Utilization (%)	71.4	86.7	21.4
Setup Frequency (per Week)	42	28	-33.3
Idle Time (Hours/Week)	31.8	18.5	-41.8
Cycle Time (Hours)	8.7	6.5	-25.3
Yield (%)	93.2	96.4	3.4
Inventory Cost ($/Month)	24,500	19,300	-21.2
OEE (%)	67.8	82.1	21.1

The optimized system increased throughput from 1,120 to 1,342 units per day, representing a 19.8% improvement. Machine utilization improved from 71.4% to 86.7%, indicating more effective resource utilization and reduced idle capacity. A significant reduction was observed in setup frequency, which decreased from 42 to 28 per week (33.3%). This reduction directly contributed to lower downtime and improved production continuity. Consequently, idle time decreased by 41.8%, while cycle time reduced by 25.3%, reflecting smoother and more efficient production flow. Inventory holding cost also declined by 21.2%, driven by improved batch sizing decisions and better alignment between production and demand.

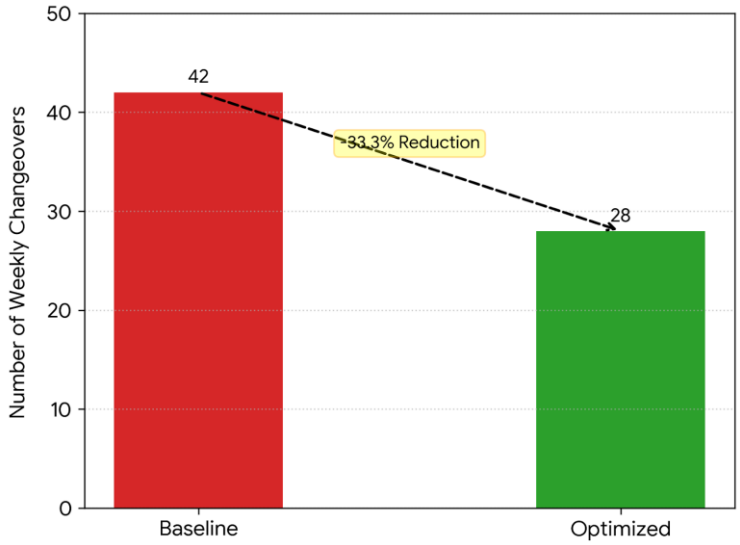

Fig. 8 Changeover Frequency Comparison (Baseline vs Optimized)

The reduction in setup frequency highlights the effectiveness of sequence-dependent optimization in minimizing non-value-added activities, which is particularly critical in high-mix manufacturing environments. Queueing-theoretic analysis was further used to evaluate system-level flow behavior and congestion.

Table .V *Queueing Performance Indicators*

Metric	**Baseline**	**Optimized**
Utilization Factor (ρ)	0.88	0.79
Average Queue Length	7.9	4.6
Waiting Time (Hours)	3.4	1.9
Work-in-Process (Units)	214	152

The utilization factor decreased from 0.88 to 0.79, indicating a more balanced and stable system with reduced congestion. Average queue length decreased by approximately 41.8%, while average waiting time reduced from 3.4 to 1.9 hours. Work-in-process inventory also dropped from 214 to 152 units, reflecting improved flow synchronization and reduced bottleneck formation. OEE analysis was conducted to evaluate overall equipment performance.

Table. VI *OEE Component Breakdown*

Component	Baseline (%)	Optimized (%)
Availability	78.5	89.4
Performance	85.1	91.7
Quality	93.2	96.4
Overall OEE	67.8	82.1

Overall OEE increased from 67.8% to 82.1%, representing a 21.1% improvement in equipment effectiveness. The most significant gain was observed in availability, primarily due to reduced setup time and improved scheduling efficiency. Performance and quality also improved, reflecting more stable production conditions and reduced operational variability.

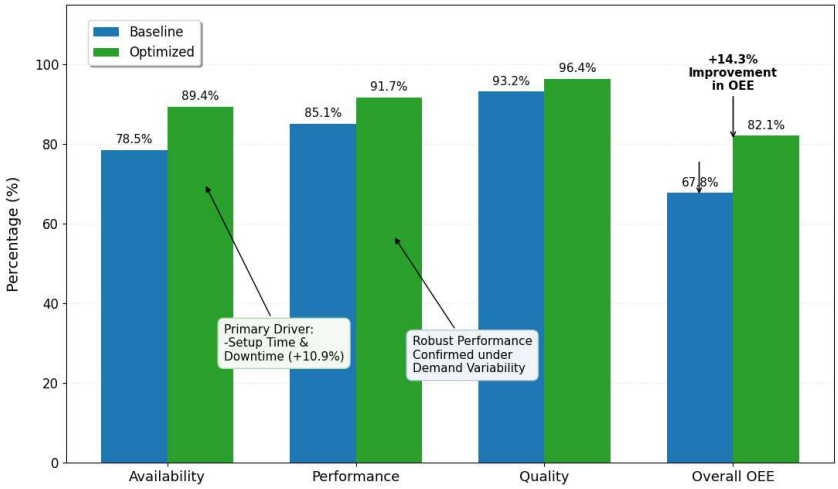

Fig. 9 Sensitivity Analysis Under Demand Variability

Sensitivity analysis under ±10%, ±20%, and ±30% demand uncertainty confirmed that the optimized policy consistently outperformed the baseline. Even under high uncertainty (±30%), throughput improvements remained above 15%, demonstrating the robustness of the proposed model in dynamic production environments.

B. Discussion

The results demonstrate that integrating batch sizing and changeover scheduling within a unified MILP framework significantly improves manufacturing performance. By simultaneously considering setup times, machine capacities, inventory constraints, and sequencing decisions, the model provides a more realistic and system-wide representation of production planning compared to conventional fixed-batch approaches. A key improvement arises from the substantial reduction in setup frequency, which directly reduces non-value-added time in high-mix manufacturing systems. This leads to higher throughput and improved machine utilization, as confirmed by gains of 19.8% and 21.4%, respectively. In addition,

reductions in idle time and cycle time indicate smoother production flow and improved operational stability. Queueing analysis further validates these improvements by showing reduced congestion, lower waiting times, and decreased work-in-process levels. The reduction in utilization factor from 0.88 to 0.79 reflects improved load balancing and reduced system pressure, contributing to more stable system behavior. Similarly, OEE results indicate balanced improvements across availability, performance, and quality dimensions. The increase in OEE from 67.8% to 82.1% highlights that performance gains are not isolated but system-wide, with availability contributing most due to reduced setup-related downtime. Overall, the findings confirm that manufacturing productivity should be treated as an integrated optimization problem rather than independent decision modules. The proposed framework demonstrates strong applicability for high-mix industries such as automotive, electronics, and medical device manufacturing.

C. Limitations and Future Work

Despite strong performance improvements, several limitations should be acknowledged.

First, the study is based on simulation-based validation rather than real industrial implementation. While simulation provides controlled evaluation, real manufacturing environments may include additional uncertainties such as machine breakdowns, labor variability, material shortages, and supply chain disruptions. Second, the model assumes relatively stable estimates of demand, processing time, and setup parameters. In practice, forecasting errors and dynamic disturbances may reduce solution accuracy. Future work should therefore consider stochastic and robust optimization approaches. Third, environmental and sustainability factors such as energy consumption and carbon emissions are not explicitly included in the objective function. Incorporating these aspects would improve alignment with green manufacturing objectives. Fourth, the queueing model is simplified and may not fully capture complex production systems with parallel machines, buffers, and re-entrant flows. Future research should extend this using queueing networks, digital twin models, or high-fidelity discrete-event simulation. Finally, integration with Industry 4.0 technologies such as IIoT, digital twins, machine learning, and reinforcement learning should be explored to enable real-time adaptive scheduling and autonomous decision-making.

V. Conclusion

This study developed an integrated optimization framework for improving productivity in multi-product manufacturing systems through joint batch sizing and changeover scheduling.

The primary objective was to reduce setup losses, minimize idle time, and enhance overall system efficiency using a combined MILP, queueing theory, and OEE-based approach. The results demonstrate that the proposed framework significantly outperforms conventional fixed-batch policies. Improvements were observed in throughput, machine utilization, and OEE, along with substantial reductions in setup frequency, cycle time, waiting time, and inventory cost. Queueing analysis confirmed reduced congestion and improved system stability, while OEE results indicated balanced improvements across availability, performance, and quality. From an application perspective, the model provides a scalable decision-support tool for high-mix manufacturing environments such as automotive, electronics, and medical device industries. It enables coordinated decision-making across batch sizing, sequencing, and resource allocation, leading to more efficient production systems. Future research should extend the framework to stochastic and robust optimization models to better handle uncertainty. Integration with Industry 4.0 technologies such as IoT-enabled monitoring, digital twins, and reinforcement learning will further enhance real-time adaptability. Additionally, incorporating sustainability metrics such as energy and emissions will improve industrial relevance. Overall, the study contributes a comprehensive and high-impact optimization framework that bridges mathematical modeling and real-world manufacturing decision-making, with strong potential for both academic and industrial applications.

VI. Reference

[1] Samouilidou, M. E., Georgiadis, G. P., & Georgiadis, M. C. (2023). Food production scheduling: A thorough comparative study between optimization and rule-based approaches. *Processes, 11*(7), 1950. https://doi.org/10.3390/pr11071950

[2] Georgiadis, G. P., Georgiadis, M. C., Pampín, B. M., & Cabo, D. (2020). Optimal production scheduling of food process industries. *Computers & Chemical Engineering, 137*, 106814. https://doi.org/10.1016/j.compchemeng.2020.106814

[3] Fattahi, P., Mehrabad, M. S., & Jolai, F. (2021). Mathematical modeling and optimization of production scheduling problems in flexible manufacturing systems. *Applied Mathematical Modelling, 89*, 1175–1196. https://doi.org/10.1016/j.apm.2020.08.027

[4] Tirkolaee, E. B., Goli, A., & Weber, G. W. (2021). Multi-objective production scheduling optimization in manufacturing systems using hybrid metaheuristics. *Applied Soft Computing, 106*, 107312. https://doi.org/10.1016/j.asoc.2021.107312

[5] Zhang, Y., Wang, J., & Liu, S. (2021). Integrated production scheduling and lot sizing optimization in multi-product manufacturing systems under demand uncertainty. *International Journal of Production Economics, 238*, 108177. https://doi.org/10.1016/j.ijpe.2021.108177

[6] Yue, D., Gupta, Y., & Smith, R. (2022). Dynamic lot-sizing and scheduling optimization in flexible multi-product manufacturing facilities. *Computers & Chemical Engineering, 160*, 107703. https://doi.org/10.1016/j.compchemeng.2022.107703

[7] Brunaud, B., Perez, M., & Grossmann, I. E. (2020). Batch scheduling with quality-based changeovers. *Industrial & Engineering Chemistry Research, 59*(15), 7098–7112. https://doi.org/10.1021/acs.iecr.9b05629

[8] Li, X., Chen, Z., & Wang, Y. (2022). Sequence-dependent setup time reduction in flexible manufacturing systems using mixed-integer programming. *Computers & Industrial Engineering, 170*, 108259. https://doi.org/10.1016/j.cie.2022.108259

[9] Bagheri, M., Zandieh, M., & Mahdavi, I. (2021). Production scheduling considering resource capacity fluctuations and sequence-dependent setup times. *Expert Systems with Applications, 181*, 115086. https://doi.org/10.1016/j.eswa.2021.115086

[10] Chen, J., Pan, Q. K., & Gao, L. (2022). Distributed blocking flowshop scheduling with sequence-dependent setup times: Heuristics and optimization approaches. *European Journal of Operational Research, 300*(2), 553–569. https://doi.org/10.1016/j.ejor.2021.08.027

[11] Kopanos, G. M., Puigjaner, L., & Georgiadis, M. C. (2020). Efficient production scheduling in multiproduct plants considering sequence-dependent setup operations. *Computers & Chemical Engineering, 134*, 106691. https://doi.org/10.1016/j.compchemeng.2019.106691

[12] Nelfiyanti, N., Sari, D. P., & Widodo, E. (2025). Adoption and impact of quick response manufacturing across industrial sectors: A literature review. *Journal of Optimization in Industrial Engineering*. https://doi.org/10.1007/s43069-025-00463-8

[13] Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., & Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. *Saudi Journal of Engineering and Technology*, 10(4), 169–178

[14] Azad, M. A. (2025). Evaluating the role of lean manufacturing in reducing production costs and enhancing efficiency in textile mills. *TechRxiv*. https://doi.org/10.36227/techrxiv.175459830.02641032/v1

[15] Shaikat, M. F. B. (2025). Pilot deployment of an AI-driven production intelligence platform in a textile assembly line. *TechRxiv*. https://doi.org/10.36227/techrxiv.175203708.81014137/v1

[16] Islam, R. (2025, October 15). Integration of IIoT and MIS for smart pharmaceutical manufacturing . *TechRxiv*. https://doi.org/10.36227/techrxiv.176049811.10002169

[17] Alam, MS (2025, October 21). Data-driven production scheduling for high-mix manufacturing environments. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107775.59550104/v1

[18] Alam, M. S. (2025). Real-Time Predictive Analytics for Factory Bottleneck Detection Using Edge-Based IIoT Sensors and Machine Learning. In *IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 1053–1064). https://doi.org/10.5281/zenodo.17769890

[19] Kausik, A. K., Rashid, A. B., Baki, R. F., & Maktum, M. M. J. (2025). Machine learning algorithms for manufacturing quality assurance: A systematic review of performance metrics and applications. *Array, 25*, 100393. https://doi.org/10.1016/j.array.2025.100393

[20] Del Gallo, M., Poler, R., & Ciarapica, F. E. (2026). A conceptual model for provider production scheduling in a manufacturing-as-a-service system using deep reinforcement learning. *International Journal of Production Management and Engineering, 14*(1), 113–127. https://doi.org/10.4995/IJPME.2026.24341

[21] Samouilidou, M. E., Georgiadis, G. P., & Georgiadis, M. C. (2024). A multi-bucket time representation framework for optimal scheduling in beverage production facilities. *Computers & Chemical Engineering, 185*, 108696. https://doi.org/10.1016/j.compchemeng.2024.108696

[22] Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., & Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. *Saudi Journal of Engineering and Technology*, 10(4), 179–188

[23] Al Sany, S. M. A., Rahman, M., & Haque, S. (2025). ERP–MIS Integration for Intelligent Apparel Production Planning. *World Journal of Advanced Engineering Technology and Sciences,* 17(1), 145–156. https://doi.org/10.30574/wjaets.2025.17.1.1387

[24] Nahar, S. (2025). Optimizing HR management in smart pharmaceutical manufacturing through IIoT and MIS integration. *World Journal of Advanced Engineering Technology and Sciences,* 17(03), 240–252. https://doi.org/10.30574/wjaets.2025.17.3.1554

[25] Fazle, A. B. (2025). AI-driven predictive maintenance and process optimization in manufacturing systems using machine learning and Hossainsensor analytics. *Global Journal of Engineering and Technology Advances*, 25(03), 153–167. https://doi.org/10.30574/gjeta.2025.25.3.0349

[26] Taimun, M. T. Y., Alam, M. S., & Fareed, S. M. (2026). Digital twin-enabled predictive maintenance for textile and mechanical systems. *World Journal of Advanced Engineering Technology and Sciences,* 18(01), 187–203. https://doi.org/10.30574/wjaets.2026.18.1.0001

[27] Fazle, A. B., Taimun, M. T. Y., Fareed, S. M., & Alam, M. S. (2026). Ergonomic and automation based process redesign in industrial workstations. *Global Journal of Engineering and Technology Advances,* 26(01), 091–108. https://doi.org/10.30574/gjeta.2026.26.1.0010

[28] Alam, M. S., Fareed, S. M., Fazle, A. B., & Taimun, M. T. Y. (2026). Intelligent material flow optimization using IoT sensors and RFID tracking. *Global Journal of Engineering and Technology Advances*, 26(01), 109–125. https://doi.org/10.30574/gjeta.2026.26.1.0011

[29] Islam, R. (2026). AI-Integrated Management Information Systems for Manufacturing and Supply Chain Risk Mitigation. *Zenodo.* https://doi.org/10.5281/zenodo.18349501

[30] Fareed, S. M. (2026). AI-driven digital twin framework for safety stock optimization in multi-stage manufacturing systems [Preprint]. *Zenodo*. https://doi.org/10.5281/zenodo.19332500

[31] Fazle, A. B. (2026). Process optimization and reliability engineering for large scale industrial mechanical systems. *Zenodo.* https://doi.org/10.5281/zenodo.19355577

[32] Karim, F. M. Z. (2026). Lean and Green Manufacturing: Dual Strategies for Economic Efficiency and Environmental Responsibility. *Zenodo*. https://doi.org/10.5281/zenodo.19368900

[33] Fareed, S. M., Alam, M. S., Taimun, M. T. Y., & Fazle, A. B. (2026). Smart supply chain optimization using IoT and predictive analytics. *International Journal of Scientific Research and Engineering Development (IJSRED)*, 9(1), 189–201. https://doi.org/10.5281/zenodo.18222645

[34] Shaikat, M. F. B., & Happy, A. T. (2026). Architectural flexibility in powertrain manufacturing: A review of reconfigurable assembly lines for concurrent ICE and electric drive unit production. *Zenodo.* https://doi.org/10.5281/zenodo.20293683

[35] Azad, M. A. (2025). Optimizing supply chain efficiency through lean Six Sigma: Case studies in textile and apparel manufacturing. *Preprints*. https://doi.org/10.20944/preprints202508.0013.v1

[36] Azad, M. A. (2025). Leveraging supply chain analytics for real-time decision making in apparel manufacturing. *TechRxiv.* https://doi.org/10.36227/techrxiv.175459831.14441929/v1

[37] Rahmatullah, R. (2025). Smart agriculture and Industry 4.0: Applying industrial engineering tools to improve U.S. agricultural productivity. *World Journal of Advanced Engineering Technology and Sciences,* 17(1), 28–40. https://doi.org/10.30574/wjaets.2025.17.1.1377

[38] Hasan, E. (2025). Big Data-Driven Business Process Optimization: Enhancing Decision-Making Through Predictive Analytics. *TechRxiv*. October 07, 2025. 10.36227/techrxiv.175987736.61988942/v1

[39] Hossain, M. T. (2025). AI-Augmented Sensor Trace Analysis for Defect Localization in Apparel Production Systems Using OTDR-Inspired Methodology. *In IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 1029–1040). https://doi.org/10.5281/zenodo.17769857

[40] Uddin, M. N. (2026). AI-driven demand forecasting & inventory optimization for multi-region dealer and retail distribution network. *Zenodo*. https://doi.org/10.5281/zenodo.19473456

[41] Hossain, M. T. (2025). Data-driven optimization of apparel supply chain to reduce lead time and improve on-time delivery. *World Journal of Advanced Engineering Technology and Sciences,* 17(03), 263–277.https://doi.org/10.30574/wjaets.2025.17.3.1556

[42] Karim, F. M. Z. (2025). Integrating quality management systems to strengthen U.S. export-oriented production. *Global Journal of Engineering and Technology Advances,* 25(03), 183–198. https://doi.org/10.30574/gjeta.2025.25.3.0351

[43] Ahmed, M. (2026). Resilient global apparel supply chains and their role in stabilizing U.S. retail distribution systems. *Zenodo*. https://doi.org/10.5281/zenodo.19471117

[44] Ahmed, M. (2026). Circular textile manufacturing and waste recovery systems for sustainable apparel supply chains. *Zenodo*. https://doi.org/10.5281/zenodo.19559470

[45] Hossain, M. I. (2026). Enabled digitalization of container vessel navigation and U.S. port operations using real-time AIS and operational data for shipping and supply chain optimization. *Zenodo.* https://doi.org/10.5281/zenodo.19441203

[46] Ahmed, M. (2026, March 16). Operational risk management in international apparel manufacturing networks. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.6560164

[47] Rahman, M., Alam, M. S., Al Sany, S. M. A., & Nahar, S. (2026, February 24). Enterprise AI driven data management framework for cross industry decision intelligence and operational optimization. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.6330258

[48] Nahar, S., Sany, S. M. A. A., Rahman, M., & Alam, M. S. (2026, March 3). Digital twin-based AI data management system for real-time industrial and business process optimization. *SSRN Electronic Journal*. https://ssrn.com/abstract=6337579

[49] Nahian, A. E. (2026). Optimization of financial resource allocation using management information systems and linear programming models. *Zenodo*. https://doi.org/10.5281/zenodo.20036771