Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

SIMULATION-BASED JOB SHOP SCHEDULING TO MINIMIZE RESOURCE UNCERTAINTIES IN MANUFACTURING ENVIRONMENT

Md Abubakar Siddique[1], Selim Molla[2], Amit Joe Lopes[1], and Md Fashiar Rahman[1]

[1]Dept. of Industrial, Manufacturing, and Systems Engineering, The University of Texas at El Paso, Texas, USA
[2]Dept. of Mathematics, The University of Texas at El Paso, Texas, USA

ABSTRACT

The complexity of job shops arises from variable product routing, machine reliability, and operator learning, requiring intelligent scheduling strategies. Traditional models rely on static rules such as first-available assignment, often ignoring dynamic processing times and learning effects. This paper proposes a Data-Driven Job Shop Scheduling (DDJSS) framework that dynamically selects machines based on real-time resource status. The framework is tested in FlexSim under four scenarios: (1) traditional first-available assignment, (2) random assignment, (3) DDJSS, and (4) minimum processing time without learning. Performance is evaluated using waiting time, queue length, throughput, work-in-process (WIP), utilization, and tardiness. Results demonstrate that DDJSS significantly improves workload balance, reduces queues, and minimizes WIP. The throughput increased by over 144% and 348%, for some exemplary jobs, compared to the traditional scenario. This study highlights the value of integrating learning behavior and data-driven assignments for improving decision-making in flexible job shop environments.

1 INTRODUCTION

Job shop scheduling has long been a pivotal concern in optimizing manufacturing systems due to its inherent complexity and high impact on production efficiency. In job shops, multiple product types follow unique routing sequences through different machines, often with dynamic arrival times and machine breakdowns. One critical factor that exacerbates this complexity is resource uncertainty, which refers to unpredictable variations in machine availability, operator performance, and processing times due to learning effects, maintenance schedules, or external disruptions. Accurately identifying and mitigating these uncertainties is essential for maintaining consistent throughput and reducing job tardiness. Arisha et al. (2001) emphasized that the combinatorial nature of job shop problems often makes them NP-hard and difficult to solve with traditional methods. This complexity has spurred extensive research to improve scheduling efficiency using innovative modeling and optimization approaches, particularly in environments that demand high flexibility and adaptability. One of the primary advancements in this field has been the integration of Discrete Event Simulation (DES) into scheduling decision-making. Simulation allows for evaluating different scheduling rules and system behaviors under uncertainty, providing a practical complement to optimization models. Mahdavi et al. (2010) developed a simulation-based DSS combining discrete-event simulation with an event–condition–action (ECA) controller. The system uses real-time data to adaptively coordinate decisions and optimize performance, emphasizing responsiveness and multi-criteria control in flexible job shops. Similarly, Vinod and Sridharan (2010) evaluated the effectiveness of due-date assignment methods and scheduling decision rules through DES models for dynamic job shop environments, emphasizing the value of simulation in environments with high variability.

Xiong et al. (2022) reviewed job shop scheduling models and identified key gaps such as poor handling of complex constraints, limited support for dynamic system behavior, and the lack of unified evaluation standards. They recommended AI, hybrid algorithms, and simulation-based approaches to overcome these issues. Zhao and Zhang (2021) incorporated deep reinforcement learning into job-shop production control systems, achieving dynamic adaptability by training intelligent agents to learn optimal dispatching and routing behaviors in real-time. In parallel, mathematical modeling and metaheuristics have been widely adopted for scheduling. Shen and Yao (2014) applied multi-objective evolutionary algorithms in dynamic flexible job shops, emphasizing adaptability under complex and volatile manufacturing conditions. Amiri et al. (2018) extended this approach using simulation optimization for resource assignment and sequencing under uncertainty, integrating stochastic resource constraints. Ojstersek et al. (2019) explored the synergy of mathematical and simulation modeling in improving interactivity within scheduling solutions, particularly focusing on flexible job shop environments. To ensure standardized performance evaluation across these various methods, this study follows the established metrics outlined by Pinedo (2016), including throughput, queue length, waiting time, tardiness, and resource utilization.

FlexSim is a discrete-event simulation (DES) software platform widely used for modeling, analyzing, and optimizing manufacturing and logistics systems. It provides a 3D visual environment and supports customizable logic for simulating complex workflows, machine behaviors, and resource interactions across diverse industrial scenarios. Wu et al. (2010) and Wang and Chen (2016) used FlexSim models for production line simulation and logistics system optimization, respectively. These studies highlighted FlexSim's value in identifying bottlenecks, rebalancing layouts, and simulating alternative work routing strategies. Lewicki et al. (2021) applied FlexSim to enhance process transparency and evaluate smart factory principles under Industry 4.0, particularly addressing workforce allocation and scheduling across varying shifts.

Several studies also investigated system reliability, maintainability, and workforce dynamics using simulation. Aliyu and Mokhtar (2021) focused on reliability and maintainability optimization using FlexSim by modeling machine failure patterns and repair times through MTBF/MTTR distributions. Krynke (2021) demonstrated the application of FlexSim in workforce scheduling, optimizing personnel placement to reduce idle time and improve flow continuity. Similarly, Rahman et al. (2023) proposed a simulation framework for line balancing under demand uncertainty, showcasing how task sequencing and operator assignments affect overall system throughput and responsiveness. In addition to system-level scheduling, learning curves have emerged as critical factors in job shop performance. Mosheiov and Sidney (2002) examined general job-dependent learning effects, showing that operator proficiency increases over time, reducing processing time. Glock et al. (2019) presented a systematic literature review, noting that ignoring learning dynamics can significantly distort productivity and throughput predictions in simulations and planning models.

Domain-specific applications and hybrid simulation have also provided new insights. Gupta and Sivakumar (2004) studied job shop scheduling within semiconductor manufacturing, focusing on cleanroom constraints and batch process requirements. Supsomboon and Vajaisarnun (2016) used simulation to improve job shop performance in machine parts manufacturing, adjusting routing sequences and work-in-process (WIP) levels. Cai et al. (2012) applied FlexSim to simulate underground longwall mining operations, showing how discrete-event logic can replicate the dependencies of mobile equipment, conveyor flows, and breakdowns in mining cycles. Rodrigues et al. (2019) combined agent-based modeling with DES to simulate decentralized scheduling decisions in job shop systems. Yan and Wang (2007) introduced a rule-based optimization framework that integrates simulation feedback to fine-tune dispatching policies dynamically. Such hybrid approaches bridge the gap between predictive modeling and reactive control in real-time shop floors.

While prior studies have advanced job shop scheduling using simulation and AI, few have dynamically integrated operator learning effects into machine assignment. Most models rely on resource availability or static assignment rules, overlooking the potential performance gains from allocating jobs based on operator experience and shorter processing times. This research addresses that gap by developing a FlexSim model that allocates machines based on minimized processing times while accounting for operator learning effects.

The study's main objective is to enhance scheduling performance in variable job shop environments by incorporating real-time learning-adjusted data. The novelty lies in the design of the Data-Driven Job Shop Scheduling (DDJSS) algorithm, which uses current system data to dynamically assign machines. A FlexSim simulation evaluates the DDJSS against three alternative scenarios, with performance assessed via metrics such as waiting time, queue length, tardiness, resource utilization, and throughput.

2 PROBLEM STATEMENT

In a job shop production system, multiple products with unique routing sequences and non-uniform arrival patterns must be processed across various workstations. This variability creates significant challenges in assigning jobs efficiently. Idle machines may remain underutilized despite job backlogs due to rigid scheduling that overlooks processing time differences. Selecting machines based on the shortest processing time could improve performance, but such dynamic decisions require appropriate modeling. Additionally, operator efficiency evolves over time due to learning effects, which must be captured to reflect realistic improvements in productivity and cycle time.

Another key factor is machine reliability, as unexpected breakdowns disrupt flow and increase WIP. The ability to reassign jobs during such failures is crucial for maintaining system performance. These complexities necessitate a simulation-driven approach that incorporates processing variability, operator learning, and equipment reliability. This enables better resource allocation, dynamic scheduling, and overall optimization. The goal is to improve utilization by identifying overloaded or underused resources and adjusting capacity accordingly.

3 CASE STUDY

This case study investigates a simulation-based job shop scheduling environment developed in FlexSim, incorporating machine availability, operator learning curves, and complex product-specific routing. The objective is to analyze system behavior under realistic production dynamics and identify opportunities for improving throughput, resource utilization, and decision-making logic. This hypothetical job shop processes five different product types, each with distinct routing sequences and varying frequencies of order arrivals. The jobs arrive at the facilities following an exponential distribution with a mean interarrival time of 4 minutes with a specific product mix order distribution as shown in Table 1.

Table 1: Product Routing Sequences and Order Proportions.

Product	Routing Sequence	Order %
Automotive Engine Brackets	Milling → Drilling → Shaping → Lathe	25%
Aerospace Turbine Blades	Lathe → Milling → Drilling → Grinding → EDM	15%
Precision Gears	Lathe → Shaping → Milling → Drilling	20%
Medical Implants (Titanium)	Milling → Drilling → Lathe → Polishing	18%
Hydraulic Cylinder Pistons	Lathe → Milling → Drilling → Shaping	22%

The facility comprises several machining stations, each equipped with a specific number of machines to support various production processes. The Lathe station consists of five machines, while the Drilling and Shaping stations each contain three machines. The Milling station is equipped with four machines to accommodate high-volume tasks. For precision finishing, the Grinding and Polishing stations have two machines each. Additionally, there is a single Electrical Discharge Machining (EDM) unit, which is used for specialized high-precision operations. This setup supports a wide range of product routings with diverse processing requirements.

3.1 Operational Data

The values presented in Tables 2 and 3 were determined using synthetic yet representative data, designed to reflect typical trends observed in job shop environments. These values are not extracted from a specific industrial dataset, but instead derived through educated assumptions.

Table 2 summarizes the reliability and maintainability parameters assigned to each machine type in the simulation model. Breakdowns are modeled using exponential distributions based on the Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR). MTBF indicates the average time between failures, while MTTR reflects the downtime needed for repairs. These parameters are vital for accurately modeling machine availability and evaluating their effects on production flow and resource utilization.

Table 2: Machine-Specific Breakdown and Repair Characteristics.

Machine Type	Lathe	Milling	Drilling	Shaping	Grinding	Polishing	EDM
MTBF (min)	10,000	7,000	8,800	8,200	4,000	5,200	3,500
MTTR (min)	300	360	240	300	420	360	480

The inclusion of learning curves allows the simulation to capture realistic human factors, such as adaptation speed and productivity growth, which are critical for accurate performance evaluation and decision-making in job shop environments. Table 3 presents the average Learning Rates (LR) assigned to each machine type in the simulation model, reflecting the progressive improvement in operator efficiency through repeated task execution.

Table 3: Average Learning Rates by Machine Type.

Machine Type	Lathe	Milling	Drilling	Shaping	Grinding	Polishing	EDM
Learning Rate	80%	85%	88%	86%	82%	90%	85%

Processing times vary by product, machine, and operation type. To reflect real-world variability, triangular distributions (minimum, mode, maximum) were assigned to each machine–product pair. These capture uncertainty due to material handling, machine condition, and operator performance. For instance, automotive engine brackets may take 5–15 minutes (mode: 10) on Lathe-1, but 9–14 minutes on Lathe-3. Each product follows a distinct processing path using a specific set of machines, with operations like EDM, polishing, or grinding included only when applicable (e.g., turbine blades are not polished).

4 METHODOLOGY

This section outlines the modeling principles and implementation of the job shop simulation system using FlexSim. The methodology comprises three key components: the theoretical modeling of operator learning curves, the Data Driven Job Shop Scheduling (DDJSS) algorithm, and four simulation scenarios to make a comparison. In this study, resource uncertainty is explicitly defined and addressed across three dimensions: machine availability uncertainty, captured through random breakdown patterns and varying MTBF/MTTR values; operator learning uncertainty, modeled using learning curves that adjust processing times based on accumulated experience; and dynamic resource status, represented by real-time resource utilization and queuing data within the simulation environment.

4.1 Learning Curve and Operator Efficiency Modeling

The processing time reduction due to operator learning is modeled using a power-law (exponential) learning curve, a well-established empirical relationship in manufacturing systems introduced by Wright (1936). The fundamental assumption is that each time cumulative production doubles, the processing time per unit decreases by a fixed percentage is known as the learning rate (LR). The general form of the learning curve is:

$$y = ax^{-b} \tag{1}$$

where, y is the hours required to produce the *x-th* unit, a is the time to produce the first unit, x is the cumulative number of units produced, and b is the learning index, defined as:

$$b = \frac{\log\,(learning\ rate)}{\log\,(2)} \tag{2}$$

For example, if a job's first unit time is 12 minutes (from a triangular distribution) and the learning rate is 90% (b≈- 0.152), then after 8 completed units, the adjusted time is: $y=12\times8^{-0.152}\approx8.75$ minutes. This reflects improved efficiency as the operator gains experience.

4.2 Data Driven Job Shop Scheduling (DDJSS) Algorithm

Algorithm 1 presents the Data-Driven Job Shop Scheduling (DDJSS) algorithm used for real-time machine assignments.

Algorithm 1: DDJSS

```
Function DDJSS(product):
    Input: product arriving at the parallel workstation unit;
    Output: Successful processing of the product through workstations;
    Retrieve or generate predicted processing times PT[i] for all
     workstations;
    while product not yet successfully processed do
        Check availability of all workstations;
        if all workstations are busy then
            Send product to Waiting Area;
            Wait until any workstation becomes available;
            continue;
        end
        Select the available workstation k with the smallest PT[k];
        if product is rerouted after breakdown then
            Retrieve stored PT[k];
            if PT[k] > remainingTime then
                processingTime ← remainingTime;
            else
                processingTime ← PT[k];
            end
        else
            processingTime ← PT[k];
        end
        Start processing on workstation k for processingTime;
        if breakdown occurs then
            Calculate elapsedTime and remainingTime;
            Store remainingTime;
            Requeue product to the parallel workstation;
        else
            Route product to the next step;
            break;
        end
    end
end
```

To improve machine selection and routing in dynamic job shop environments, the proposed DDJSS algorithm uses real-time system data such as machine availability, the lowest processing time required among available machines, and the learning effect of experienced operators to select the machine with the lowest estimated processing time. While the algorithm structure follows a rule-based implementation, its logic is inherently data-driven in execution, allowing it to adapt to breakdowns, operator learning, and workload changes. Unlike AI-based or simulation optimization methods that require extensive data and complex model integration, DDJSS enables interpretable, low-latency decisions, making it practical for real-time use in variable, operator-driven settings.

Jobs are selected from the waiting area based on a First-Come-First-Served (FCFS) policy to preserve fairness and prevent starvation in the queue. The term “minimum predicted processing time” refers to the learning-adjusted expected processing duration required to complete the operation on a given machine. It does not include current queue time or machine state, but reflects the pure processing time adjusted for operator learning effects. This value is not equivalent to minimum completion time, which would include additional delays like waiting or setup time. The selection logic prioritizes the machine expected to process the product in the least amount of time once available, improving responsiveness without preemptively predicting full system delay. The Decision Flowchart for DDJSS Algorithm is shown in Figure 1.

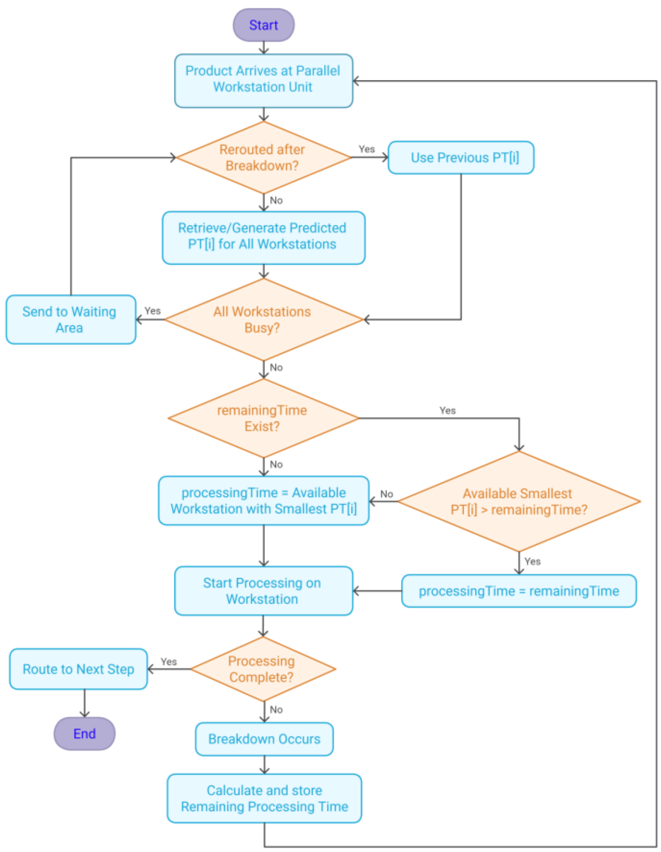

Figure 1: Decision Flowchart for Data Driven Job Shop Scheduling (DDJSS) Algorithm.

4.3 Developing Simulation Scenarios in FlexSim

To assess the effectiveness of the proposed decision algorithm, four simulation models were developed in FlexSim. Figure 2 illustrates the general FlexSim layout used for all four scenarios. This layout includes multiple parallel machine groups (e.g., Lathe, Milling, Drilling) and intermediate waiting areas. While the visual layout remains identical across the scenarios, the key difference lies in the scheduling logic.

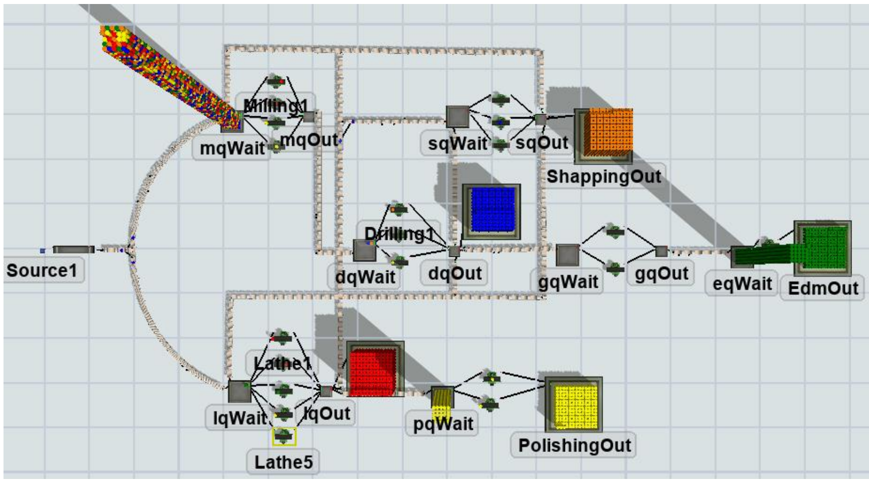

Figure 2: FlexSim Layout Used in All Scenarios.

4.3.1 Scenario 1: Traditional Job Shop Scheduling Process

This scenario mimics a traditional job shop environment where machine selection for each job operation is based solely on first-available machine logic. In this case, we did not consider machine-specific processing times, and learning curves for selecting a machine for a specific job. It represents the status quo or legacy system.

4.3.2 Scenario 2: Job Shop Scheduling Process with Random Assignment

In this scenario, job operations are assigned randomly to any available machine at a given station. Unlike the first-available logic in Scenario 1, this method introduces randomness without considering machine availability, processing time, or operator skill. It serves as a baseline to evaluate the impact of more optimized scheduling strategies.

4.3.3 Scenario 3: Proposed System – Data Driven Job Shop Scheduling (DDJSS)

The proposed model implements the DDJSS algorithm, which dynamically assigns jobs to machines based on the lowest predicted processing time, adjusted for operator learning, machine availability, and queue conditions. This approach improves routing decisions by considering breakdowns, rerouted jobs, and real-time system status, aiming to reduce delays and balance workload efficiently.

4.3.4 Scenario 4: Job Shop Scheduling with Minimal Processing Time Assignment

In this scenario, job operations are assigned to machines based on the minimum estimated processing time, without accounting for learning curve effects. Unlike the DDJSS approach, this model does not adjust for operator experience but still considers machine availability. It aims to optimize scheduling by minimizing processing time while maintaining a simplified logic for comparative analysis.

5 EXPERIMENTAL RESULTS

This section presents a comparative analysis of four scheduling scenarios implemented in FlexSim, executed over a simulated production period of one month (44,640 minutes). All scenarios share identical system configurations, including an exponential interarrival time distribution with a mean of 4 minutes, ensuring a consistent job inflow across models.

5.1 Queue Analysis: Waiting Time and Queue Length

Table 4 compares average waiting times across scenarios. The traditional model (Scenario 1) showed major delays, particularly in polishing (pqWait: 10,663.53 min), EDM (eqWait: 15,263.04 min), and milling (mqWait: 3,783.57 min). Scenario 2 performed similarly or worse, with pqWait rising to 11,622.96 min. Scenario 4 moderately reduced delays (e.g., mqWait: 1,236.43 min) by selecting minimum processing times. In contrast, Scenario 3 (DDJSS) significantly minimized waiting times across all stations, pqWait to 7.83, eqWait to 21.49, and mqWait to just 0.47 demonstrate the impact of learning-adjusted, data-driven scheduling.

Table 4: Average Waiting Time in Queue.

Object	Scenario 1	Scenario 2	Scenario 3	Scenario 4
lqWait	0.93	28.39	0.53	1.31
mqWait	3,783.57	3,552.89	0.47	1,236.43
dqWait	6.14	56.92	0.58	3.26
sqWait	1.98	20.16	0.47	2.09
gqWait	20.28	104.15	5.51	21.24
pqWait	10,663.53	11,622.96	7.83	8.41
eqWait	15,263.04	14,659.57	21.49	1,334.35

Table 5 presents the average queue content. Scenarios 1 and 2 exhibited high queue accumulation due to poor load balancing. For instance, the polishing queue (pqWait) averaged 400.45 and 451.23 jobs in Scenarios 1 and 2, respectively, while the EDM queue (eqWait) reached 479.08 and 481.04. The milling queue (mqWait) also showed severe congestion with 946.74 jobs in both scenarios. Scenario 4 reduced queue sizes moderately, but critical stations like milling (mqWait = 1,067.46) and EDM (eqWait = 130.55) still experienced notable accumulation. In contrast, Scenario 3 (DDJSS) achieved near-zero queue content across all stations. For example, pqWait = 0.09 and mqWait = 0.01 indicate smoother job flow and effective congestion control through learning-adjusted scheduling.

Table 5: Average Content in Queue.

Object	Scenario 1	Scenario 2	Scenario 3	Scenario 4
lqWait	0.22	6.59	0.00	0.15
mqWait	946.74	946.26	0.01	1,067.46
dqWait	1.29	11.87	0.02	0.97
sqWait	0.30	2.96	0.00	0.25
gqWait	0.63	3.44	0.04	0.63
pqWait	400.45	451.23	0.09	0.14
eqWait	479.08	481.04	1.04	130.55

These results reflect the importance of smart scheduling and dynamic assignment strategies in minimizing idle time, balancing workload, and enhancing system responsiveness.

5.2 WIP Levels

Table 6 compares the WIP levels for five key product categories tracked through their respective output queues: LatheOut (Automotive Engine Brackets), DrillingOut (Precision Gears), ShappingOut (Hydraulic Cylinder Pistons), PolishingOut (Medical Implants), and EdmOut (Aerospace Turbine Blades). Scenarios 1 and 2 exhibit extremely high WIP accumulation due to static and random machine assignment. For example, WIP levels for Precision Gears remain constant at 1,300 units, while Medical Implants exceed 1,240 units across both scenarios. Scenario 4 slightly improves system responsiveness by prioritizing machines with shorter processing times; however, queues like Automotive Engine Brackets still show 522 units and Aerospace Turbine Blades reach 488 units, indicating incomplete relief of congestion. In contrast, Scenario 3 (DDJSS) achieves a dramatic reduction in WIP down to just 1 unit for Medical Implants, 2 for Aerospace Blades, and only 3 for Engine Brackets demonstrate effective workload balancing, improved system flow, and real-time responsiveness enabled by data-driven scheduling.

Table 6: Comparison of WIP levels.

Product	Output Queue	Scenario-1	Scenario-2	Scenario-3	Scenario-4
Automotive Engine Brackets	LatheOut	491	496	3	522
Precision Gears	DrillingOut	1,300	1,300	8	646
Hydraulic Cylinder Pistons	ShappingOut	361	370	1	426
Medical Implants (Titanium)	PolishingOut	1,245	1,246	1	400
Aerospace Turbine Blades	EdmOut	409	445	2	488

5.3 Tardiness

The due dates for all jobs were assumed to follow a triangular distribution with parameters (8000, 10000, 12000), reflecting realistic variability in delivery expectations. Table 7 summarizes the average job tardiness across all scenarios. Scenarios 1 and 2, which use static and random machine assignment, exhibit high tardiness of 1,020.18 minutes and 1,118.98 minutes, respectively indicate inefficient routing and poor delivery reliability. Scenario 4, which uses a minimal processing time heuristic, reduces tardiness to 406.12 minutes, demonstrating partial improvement. However, Scenario 3 (DDJSS) eliminates tardiness entirely, achieving 0 minutes of delay. This outcome underscores the value of learning-adjusted, data-driven scheduling in effectively meeting delivery deadlines, improving workflow synchronization, and significantly enhancing delivery performance compared to traditional methods.

Table 7: Comparison of Tardiness Across Scheduling Scenarios.

Scenarios	Scenario-1	Scenario-2	Scenario-3	Scenario-4
Tardiness	1,020.18	1,118.98	0	406.12

5.4 Average Resource Utilization

Table 8 shows the average machine utilization percentage by type across different scheduling scenarios. While Scenarios 1 and 2 maintain high machine utilization, Scenario 3 achieves optimal performance with minimal queues despite low utilization in several stations (e.g., Lathe, Grinding, Polishing). This suggests effective workload balancing and points to possible overcapacity, indicating that some machines could be reduced without affecting overall system efficiency. Scenario 4 maintains moderately high utilization with improved efficiency, showing better resource use than the baseline but still lacking the adaptive balance achieved by DDJSS.

Table 8: Average Resource Utilization Percentage Across Scenarios.

Scenarios/Machine Type	Lathe	Milling	Drilling	Shaping	Grinding	Polishing	EDM
Scenario-1	57.66	96.75	84.95	56.59	44.54	94.11	80.93
Scenario-2	58.52	96.65	85.16	56.27	44.30	94.06	80.89
Scenario-3	5.75	20.52	24.05	12.04	10.26	14.74	29.96
Scenario-4	49.73	96.79	80.57	50.89	41.43	29.92	79.83

5.5 Throughput Performance

Table 9 presents the throughput of five primary product categories tracked through their respective output queues. Compared to Scenario 1 (traditional model), Scenario 3 (DDJSS) achieved the highest total throughput of 11,283 units, representing a 49.6% improvement over the baseline output of 7,541 units. This gain stems from the integration of adaptive machine pairing and learning-adjusted scheduling logic. The most significant improvements were observed at PolishingOut and EdmOut, where outputs increased by over 144% and 348%, respectively. These stations had previously suffered from major queuing delays and inefficiencies. By prioritizing machines based on learning-adjusted processing times in real time, DDJSS alleviated these bottlenecks and improved overall resource utilization.

Table 9: Throughput Comparison Across Scenarios.

Product	Output Queue	Scenario-1	Scenario-2	Scenario-3	Scenario-4
Automotive Engine Brackets	LatheOut	2,293	2,261	2,845	2,235
Precision Gears	DrillingOut	1,997	1,875	2,227	1,819
Hydraulic Cylinder Pistons	ShappingOut	2,048	2,026	2,535	1,983
Medical Implants (Titanium)	PolishingOut	842	839	2,060	1,685
Aerospace Turbine Blades	EdmOut	361	361	1,616	1,015
Total Throughput		7,541	6,523	11,283	8,737

Other stations also showed notable gains: LatheOut improved by over 24%, DrillingOut by 11.5%, and ShappingOut by nearly 24%. These results confirm the effectiveness of DDJSS in boosting throughput through smarter, data-responsive scheduling. Scenario 2, which used random machine selection, recorded the lowest throughput at 6,523 units, highlighting the consequences of unstructured decision-making. Scenario 4 achieved a moderate improvement to 8,737 units by minimizing processing times, but it lacked the dynamic adaptability of DDJSS.

5.6 Sensitivity Analysis

To ensure the reliability and stability of the proposed scheduling model, a sensitivity analysis was conducted using the FlexSim Experimenter, running 150 replications for Scenario 1 and Scenario 3. Each replication simulated 30 days (44,640 minutes) of continuous production. All replications maintained the same input conditions, including an exponential interarrival time distribution with a mean of 4 minutes. The goal was to verify whether the performance improvements observed in earlier simulations (Table 9) remained consistent across repeated trials under identical workload conditions.

Table 10 presents the statistical summary of output results, including the mean, standard deviation, and 95% confidence intervals (CIs) for each product's throughput across 150 simulation replications. The results confirm that the proposed DDJSS model consistently outperformed the traditional scheduling setup with not only higher average outputs but also reduced variability. For example, Medical Implants (Titanium) achieved an average output of 2,011 ± 41.89 under DDJSS, compared to just 833 ± 17.01 in the traditional model, representing a significant increase in both quantity and stability, as reflected in the tight confidence interval of [2004–2018] versus [831–836]. This closely aligns with the earlier result of 2,060 units reported for Scenario 3 (Table 9), indicating strong consistency across replications with a minor deviation. Similarly, Aerospace Turbine Blades improved markedly from 392 ± 19.11 to 1,672 ± 40.32, with a 95% confidence interval of [1665–1678], again highlighting the statistical reliability of the performance boost.

Table 10: Sensitivity Analysis for Throughput.

Product	Scenario-1 (Traditional)			Scenario-3 (DDJSS)		
	Mean	Std Dev	95% CI	Mean	Std Dev	95% CI
Automotive Engine Brackets	2,293	48.30	2285-2301	2,782	50.90	2774-2790
Precision Gears	1,840	50.04	1832-1848	2,230	45.63	2222-2237
Hydraulic Cylinder Pistons	2,023	40.57	2017-2030	2,454	46.02	2446-2461
Medical Implants (Titanium)	833	17.01	831-836	2,011	41.89	2004-2018
Aerospace Turbine Blades	392	19.11	389-395	1,672	40.32	1665-1678
Total Throughput	7,381			11,149		

The total throughput under Scenario 3 (DDJSS) reached 11,149 units, showing a significant improvement over the traditional mean of 7,381 units. These findings demonstrate that DDJSS not only enhances throughput but also ensures consistent and predictable system performance, validating its robustness in dynamic job shop environments.

6 CONCLUSION

This study introduced a simulation-based scheduling approach that considers machine reliability, processing time variations, and operator learning behavior to dynamically assign the jobs to machines, which addresses the complexities of modern job shop systems. By developing and comparing four simulation scenarios in FlexSim, we showed that traditional first-available assignment, random assignment, and minimum processing time without learning result in longer waiting times, higher tardiness, elevated WIP levels, and lower throughput. The proposed DDJSS approach prioritizes machine selection based on minimum learning-adjusted processing time and adapts dynamically to system states such as machine breakdowns and operator efficiency levels. The comparative analysis revealed substantial improvements in system performance, including significantly reduced queue lengths, decreased waiting times, lower tardiness, reduced WIP levels, and notably increased throughputs. These findings validate the effectiveness of simulation-driven scheduling strategies that account for human learning and machine reliability in complex manufacturing systems. However, this study has certain limitations. The simulations used synthetic data, which may limit real-world applicability. Additionally, resource adjustments based on machine utilization were not explored. Despite this, the results support the value of simulation-driven scheduling that incorporates learning and reliability. Future work could integrate real-time data and optimization techniques to enhance adaptive control.

ACKNOWLEDGEMENT

This work was partially supported by the United States (U.S.) National Science Foundation (IUSE 2216396) and the U.S. Department of Education (FIPSE P116S210004, MSEIP P120A220044). The authors wish to express sincere gratitude for their financial support

REFERENCES

Aliyu, A., A. A. Mokhtar. 2021. "Research Advances in the Application of FlexSim: A Perspective on Machine Reliability, Availability, and Maintainability Optimization". *Journal of Hunan University*, 48(9):518–563.

Amiri, F., B. Shirazi, and A. Tajdin. 2018. "Multi-Objective Simulation Optimization for Uncertain Resource Assignment and Job Sequence in Automated Flexible Job Shop". *Applied Soft Computing*, 75: 190–202.

Arisha, A., P. Young, and M. El Baradie. 2001. "Job Shop Scheduling Problem: an Overview". *International Conference for Flexible Automation and Intelligent Manufacturing (FAIM 01)*, July, Dublin, Ireland, 682 – 693.

Cai, D., E. Baafi, and I. Porter. 2012. "Modelling a Longwall Production System Using FlexSim 3D Simulation Software". In *Mine Planning and Equipment Selection*, edited by R. Singhal, E. Topal, K. Fytas, M. Yellishetty, and A. Mehrotra, 107–114. Irvine, California: The Reading Matrix Inc.

Glock, C. H., E. H. Grosse, M.Y. Jaber, and T.L. Smunt. 2018. "Applications of Learning Curves in Production and Operations Management: A Systematic Literature Review". *Computers & Industrial Engineering*, 131: 422–441.

Gupta, A. K., and A.I. Sivakumar. 2004. "Job Shop Scheduling Techniques in Semiconductor Manufacturing". *The International Journal of Advanced Manufacturing Technology*, 27(11–12): 1163–1169.

Krynke, M. 2021. "Personnel Management on the Production Line Using the FlexSim Simulation Environment". *Manufacturing Technology*, 21(5): 657–667.

Lewicki, W., M. Niekurzak, and J. Wróbel. 2024. "Development of a Simulation Model to Improve the Functioning of Production Processes Using the FlexSim Tool". *Applied Sciences*, 14(16):6957.

Mahdavi, I., B. Shirazi, and M. Solimanpur. 2010. "Development of a Simulation-Based Decision Support System for Controlling Stochastic Flexible Job Shop Manufacturing Systems". *Simulation Modelling Practice and Theory*, 18(6):768–786.

Mosheiov, G., and J. B. Sidney. 2003. "Scheduling with General Job-Dependent Learning Curves". *European Journal of Operational Research*, 147(3): 665–670.

Ojstersek, R., D. Lalic, and B. Buchmeister. 2019. "A New Method for Mathematical and Simulation Modelling Interactivity: A Case Study in Flexible Job Shop Scheduling". *Advances in Production Engineering & Management*, 14(4):435–448.

Pinedo, M. L. 2016. *Scheduling: Theory, Algorithms, and Systems*. 5th ed. Cham: Springer.

Rahman, S. M. A., M. F. Rahman, T. B. Tseng, and T. Kamal. 2023. "A Simulation-Based Approach for Line Balancing under Demand Uncertainty in Production Environment". In *2018 Winter Simulation Conference (WSC)*, 2020–2030 https://doi.org/10.1109/wsc60868.2023.10408105

Rodrigues, R. P., A. F. De Pinho, and D.C. Sena. 2019. "Application of Hybrid Simulation in Production Scheduling in Job Shop Systems". *Simulation*, 96(3): 253–268.

Shen, X., and X. Yao. 2014. "Mathematical Modeling and Multi-Objective Evolutionary Algorithms Applied to Dynamic Flexible Job Shop Scheduling Problems". *Information Sciences*, 298: 198–224.

Supsomboon, S., and A. Vajasuvimon. 2016. "Simulation Model for Job Shop Production Process Improvement in Machine Parts Manufacturing". *International Journal of Simulation Modelling*, 15(4), 611–622.

Vinod, V., and R. Sridharan. 2010. "Simulation Modeling and Analysis of Due-Date Assignment Methods and Scheduling Decision Rules in a Dynamic Job Shop Production System". *International Journal of Production Economics*, 129(1):127–146.

Wang, Y. R., and A. N. Chen. 2016. "Production Logistics Simulation and Optimization of Industrial Enterprise Based on Flexsim". *International Journal of Simulation Modelling*, 15(4):732–741.

Wright, T. P. 1936. "Factors Affecting the Cost of Airplanes". *Journal of the Aeronautical Sciences*, 3(4): 122–128.

Wu, G., L. Yao and S. Yu. 2018. " Simulation and Optimization of Production Line Based on FlexSim". *2018 Chinese Control And Decision Conference (CCDC)*, June 9th-11th, Shenyang, China, 3358-3363.

Xiong, H., S. Shi, D. Ren, and J. Hu. 2022. "A Survey of Job Shop Scheduling Problem: The Types and Models". *Computers & Operations Research*, 142: 105731.

Yan, Y., and G. Wang. 2007. "A Job Shop Scheduling Approach Based on Simulation Optimization". 2007 *IEEE International Conference on Industrial Engineering and Engineering Management*, December 2nd-4th, Singapore, 1816–1822.

Zhao, Y., and H. Zhangn. 2021. "Application of Machine Learning and Rule Scheduling in a Job-Shop Production Control System". *International Journal of Simulation Modelling*, 20(2): 410–421.

AUTHOR BIOGRAPHIES

MD ABUBAKAR SIDDIQUE is a Teaching Assistant in the Department of Industrial, Manufacturing and Systems Engineering (IMSE) at the University of Texas at El Paso (UTEP), where he is currently pursuing his M.S. degree in Manufacturing Engineering. He earned his B.Sc. in Industrial and Production Engineering from Khulna University of Engineering and Technology (KUET), Bangladesh. Mr. Siddique's research interests lie in the areas of Industrial Internet of Things (IIoT), Smart Manufacturing, and Simulation Modeling. Prior to joining UTEP, he served as a Lecturer at a university in Bangladesh, where he taught a range of courses related to manufacturing, quality control, and production engineering for five years. His email address is msiddique@miners.utep.edu.

SELIM MOLLA is a Ph.D. student in Computational Science at the University of Texas at El Paso (UTEP). He is currently working as a Research Assistant in the Department of Industrial, Manufacturing and Systems Engineering (IMSE) at UTEP. His research interests include Mathematical Modeling, Discrete Event Simulation, and Machine Learning. He holds a B.Sc. degree in Industrial and Production Engineering. Mr. Molla is actively engaged in interdisciplinary research that bridges computational methods with industrial applications. He can be reached via email at smolla@miners.utep.edu

AMIT JOE LOPES is an Associate Professor in the Department of Industrial, Manufacturing and Systems Engineering (IMSE) at The University of Texas at El Paso (UTEP). He earned his Ph.D. in Materials Science and Engineering from UTEP in 2010. Dr. Lopes has extensive research experience in areas such as Smart Manufacturing, Industry 4.0, Quality in Additive Manufacturing, and Systems Engineering applications. He has additionally instructed various courses across the fields of industrial and manufacturing engineering.His current research focuses on the application of smart manufacturing principles and augmented reality technologies to enhance operations validation and workforce training. His email address is ajlopes@utep.edu.

MD FASHIAR RAHMAN is an Assistant Professor of the Industrial, Manufacturing and Systems Engineering (IMSE) Department at The University of Texas at El Paso. He holds a Ph.D. degree in Computational Science Program. He has years of research experience in different projects in the field of image data mining, machine learning, deep learning, and computer simulation for industrial and healthcare applications. In addition, Dr. Rahman has taught various engineering courses in industrial and manufacturing engineering. His research area covers advanced quality technology, AI application in smart manufacturing, health care applications, computational intelligence/data analytics, and decision support systems. His email address is mrahman13@utep.edu and the website is https://hb2504.utep.edu/Home/Profile?username=mrahman13.