OPTIMISATION OF JOB SCHEDULING IN JOB SHOPS USING SIMULATION MODELLING

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Abstract
This study optimised job scheduling in job shop environments using simulation modelling to address challenges of high work-in-process, long flow times, and job lateness. A discrete-event simulation model was developed in SimPy to represent a five-machine job shop with stochastic job arrivals, variable processing times, routing complexity, and machine reliability. Four dispatching rules—first come first serve, shortest processing time, longest processing time, and earliest due date—were evaluated under low, medium, and high workload scenarios. Key performance indicators included average flow time, work-in-process, throughput, and late job ratio, with results validated using replication and ANOVA analysis. The results show that the shortest processing time rule consistently achieved the best performance, delivering flow times of about 1.22–1.24 days, minimizing lateness to 0.037–0.042, and increasing throughput to up to 900 jobs under high load. In contrast, FCFS and EDD recorded high lateness (0.80–0.94) and longer flow times (6–12 days). Overall, SPT improved system efficiency by over 80%, demonstrating that simulation-based scheduling is an effective decision-support tool for enhancing operational performance in job shop systems.

Keywords
Job shop, simulation, scheduling, optimisation, manufacturing industries.

1. INTRODUCTION

In the fast-paced landscape of modern manufacturing, speed, adaptability, and responsiveness have gone from competitive advantages to absolute necessities for survival. The efficiency of a factory's scheduling practices directly influences these qualities, especially on the shop floor where operational complexity can either drive excellence or cripple productivity. Central to this is job shop scheduling, a discipline tasked with orchestrating the flow of distinct, often custom, products through various machines and each job following its own unique route. At its foundation, job shop scheduling is about crafting the optimal sequence of operations to ensure that orders are completed on time, operational costs are minimized, and valuable resources like machines and labour are used to their full potential, not left standing idle [1].

Yet, the task of job shop scheduling is fraught with challenges. The environment is inherently unpredictable: processing times fluctuate due to variability in job requirements or workforce skill, machines are prone to unexpected breakdowns, and high-priority rush orders can disrupt carefully planned schedules at any moment. The diversity of products in a typical job shop means that each job might need a different machine configuration, specialized tools, or unique process steps, further complicating the scheduling puzzle. Traditional approaches such as static priority rules or inflexible scheduling algorithms often lack the agility required to address this ever-shifting complexity. They tend to break down in the face of the real-world uncertainty and dynamic changes that typify modern manufacturing setting [2].

The complexity of job shop scheduling is underscored by its classification as a Nondeterministic Polynomial Time (NP) hard problem meaning the possible combinations of job and machine assignments increase exponentially as the system scales. For even moderately sized shops, the number of theoretical schedules is astronomical, making it impossible to identify the optimal solution through brute-force calculation within a reasonable timeframe. This is especially problematic when rapid, real-time decision making is required. Simulation becomes not just advantageous but essential, as it empowers manufacturers to compare a wide array of scheduling heuristics and optimisation algorithms under realistic, variable conditions, without resorting to oversimplifications that strip away the nuances of actual production [3].

To overcome these limitations, the industry increasingly turns to simulation modelling. By creating a virtual replica, a digital twin of the production environment, manufacturers gain a powerful sandbox to trial different scheduling tactics. This digital space allows them to safely experiment with various sequencing rules, dispatching policies, and resource allocation strategies without risking disruption to actual operations. Within the simulation, bottlenecks become visible, inefficiencies are exposed, and the impacts of alternative scheduling decisions can be quantified. This proactive approach enables teams to refine their processes, reduce delays, and enhance overall machine utilization before making changes in the real world [4].

With the aid of simulation, manufacturers can rigorously test how different sequencing rules such as earliest due date, shortest processing time, first come first serve and longest processing time. They can experiment with resource management approaches, preventive maintenance schedules, and even "what-if" scenarios like sudden surges in demand or machine failures. Through this process, key performance indicators (KPIs) such as average flow time, work-in-process (WIP) and job tardiness can be tracked in detail to inform data-driven decisions. Software tool like Simpy have made it increasingly feasible to build detailed, flexible models of these complex, ever-evolving environments, even for organizations without extensive technical resources [5].

The way a factory organizes and schedules its jobs has a profound impact on its overall performance affecting not just makespan and how efficiently machines are used, but also job tardiness and, most critically, the level of WIP circulating through the shop. Allowing WIP to accumulate unchecked leads to a cascade of operational challenges: lead times stretch out, inventory costs soar, throughput slows, and the factory loses its agility to respond when customer demand fluctuates or new priorities emerge [6]. Proper WIP management is therefore essential for maintaining a competitive, responsive, and cost-effective manufacturing environment.

One of the most effective levers for keeping WIP under control is the careful and strategic assignment of job due dates. Assigning due dates is not just about meeting customer expectations; it is about orchestrating the flow of jobs through the system in a way that aligns with the factory's real processing capabilities. This demands a nuanced approach: urgent orders must be prioritized, but not at the expense of overwhelming machines or disrupting the flow of less critical work [7]. Striking this balance is crucial for keeping both WIP and customer dissatisfaction in check.

Job shops in developing economies, such as Nigeria, are plagued by chronic scheduling challenges that hinder their growth and efficiency. These issues stem from inconsistent or poorly due date assignment policies, runaway WIP, and lengthy unpredictable lead times. All too often, due dates are assigned without regard for real shop floor capacity or workload, or job shops continue to rely on simplistic, outdated scheduling rules like fixed slack that fail to adapt to the complexities of modern production. The consequences are evident: workstations become congested, queues of unfinished jobs lies across the floor, valuable space is wasted, inventory costs climb, and operations become sluggish and unreliable. High WIP does not just tie up capital and floor space; it stifles productivity, prolongs delivery times, and creates persistent stress for operators and managers alike.

The increasing demand for customized products delivered at unprecedented speed and cost-efficiency is reshaping the manufacturing landscape. Nowhere is this transformation more evident than in job shops, where high product variety, intricate routing, and shared resources reign. Unlike more predictable flow shops, where jobs proceed through machines in a set sequence, job shops must dynamically coordinate a multitude of unique workflows, each requiring its own sequence of operations and machine assignments. This complexity lies at the heart of the Job Shop Scheduling Problem (JSSP), widely recognized in operations research as one of the most challenging NP-hard problems to solve[8]. The ability to effectively address the JSSP is becoming a defining factor for manufacturing success, driving the adoption of innovative scheduling solutions and digital tools that empower organizations to remain agile, efficient, and competitive in a world where customer expectations are higher than ever.

This is where simulation modelling emerges as an indispensable tool. Through simulation, manufacturers can recreate the complex dynamics of their shop floors, including unpredictable events like equipment breakdowns, processing time variations, and jobs arriving out of sequence. Simulation platforms enable the evaluation of different scheduling rules and the integration of optimisation algorithms, offering a risk-free environment to explore how new due date strategies and WIP controls will behave under real-world scenarios[9]. With these insights, factories can move beyond intuition and trial-and-error, instead basing their decisions on robust data and predictive modelling.

From a strategic perspective, simulation-driven scheduling transforms manufacturing operations. It delivers tangible business benefits: reduced operational costs through better resource allocation, improved delivery performance that strengthens customer satisfaction, faster throughput that boosts revenue, and lower WIP inventory that frees up working capital. For small and medium-sized enterprises (SMEs), which often face tighter resource constraints and greater pressure to adapt rapidly, simulation is especially impactful. It levels the playing field by allowing these firms to optimise their production with the precision and confidence once reserved for much larger competitors. The visual and analytical power of simulation supports continuous improvement, enabling decision-makers to spot trends, anticipate problems, and plan for future growth using live data and predictive analytics [10]

Recognizing these needs, the present study aims to develop and validate a comprehensive scheduling framework rooted in simulation. By leveraging actual shop floor data and rigorously testing a range of scheduling and due date assignment strategies, the framework seeks to minimize both job processing times and overall workload. The ultimate goal is to empower manufacturers with intelligent, data-driven tools that can dynamically adapt to operational variability, thereby enhancing productivity, lowering costs, and improving delivery reliability.

There is a pressing need for an intelligent, adaptive scheduling system capable of synchronizing job release times, machine sequencing, and due date assignment based on actual shop conditions. Such a system would enable job shops to reduce WIP, cut down lead times, and improve delivery performance, all while using resources more efficiently. Overcoming the inertia of legacy practices and moving toward simulation-based, optimised scheduling is essential for Nigerian job shops seeking to compete locally and globally. The time is ripe for a paradigm shift from static, one-size-fits-all scheduling approaches to dynamic, data-informed frameworks that can anticipate and respond to the real challenges on the ground. With such innovation, job shops can break free from the cycle of inefficiency and unlock new levels of reliability, flexibility, and profitability.

The inefficiency of job shop scheduling systems, particularly in developing environments where poor due date assignment, high work-in-process (WIP), long and unpredictable lead times, and reliance on rigid or manual scheduling methods lead to congestion, delays, and poor resource utilization. Many existing approaches fail to consider the dynamic and uncertain nature of real shop floor operations, resulting in reduced productivity and unreliable delivery performance. The study lies in the application of simulation modelling as a data-driven and flexible decision-support tool that allows for the testing and comparison of different scheduling heuristics and due date assignment strategies under realistic conditions, thereby providing deeper insight into system behaviour and performance. Unlike traditional static methods, this approach integrates system variability, evaluates key performance indicators, and supports informed decision-making. Therefore, the aim of this research is to optimise job scheduling in job shop environments using simulation modelling, with a focus on reducing WIP, improving flow time, minimizing tardiness, and enhancing overall operational efficiency.

2. MATERIALS AND METHOD

2.1 Overview of Research Framework

The research framework involved several key steps: first, modelling the job shop by creating a virtual representation of the shop floor, including machines, jobs, using and simulated data on job arrivals, processing times, and machine availability; second, job routing and scheduling, where jobs were assigned to machines using earliest due date (EDD), shortest processing time (SPT), first come first serve(FCFS) and longest processing time(LPT) to determine processing order; third, performance evaluation, using KPIs such as average flow time, WIP and late job ratio to assess the effectiveness of each scheduling method; and finally, recommend the optimal strategy, identifying the heuristic that minimizes WIP while ensuring timely job completion.

2.2 Job Shop System Description

The empirical focus of this research was a medium-sized manufacturing job shop, a representative of many such facilities in emerging economy. This type of shop produces a diverse array of product types, each with unique production requirements and routings. Job arrivals occurred stochastically, reflecting real customer demand patterns, and each job had to undergo a specified sequence of operations on a subset of available machines. The facility was organized around five principal workstations: Milling, Drilling, Turning, Grinding, and Assembly, each tasked with distinct sets of operations integral to the production process.

Table 1 summarised machine specifications and characteristics to support clarity and facilitate replication of the study.

Table 1: Input data structure for the job shop [11]

Data Item	Description	Unit / Example
Machines	$M_1, M_2, \ldots, M_M$	Count, identifiers
Job Types	$J_1, J_2, \ldots, J_K$	Count, identifiers
Routing	Ordered list of machines per job	e.g J_1:$M_2 \rightarrow M_4 \rightarrow M_1$
Processing Time = Departure time - Arrival time	Time at each machine step	Minutes per operation
Setup Time (optional)	Time before processing starts	Minutes
Due Date	Target completion date/time	Datetime or minutes
Arrival Process	How and when jobs enter the system	e.g., Poisson or schedule

2.3 Data Sources and Simulation Inputs

The input data were synthetically generated using probability distributions based on standard job shop scheduling literature. This approach ensures controlled experimentation and realistic modelling of system variability in the absence of real industrial datasets.

2.3.1 Simulation modelling tool

The tools applied was SimPy for discrete-event simulation which captured the job flow and machine interactions realistically and for data analysis and visualization by processing outputs, generating charts, and evaluating system performance.

2.3.2 Simulation

.A discrete-time (daily) simulator was implemented to evaluate four dispatching rules: FCFS, SPT, LPT and EDD scheduling rules. Key performance measures are WIP, average flow time, and late job ratio.

2.3.3 Simulation Setup

Simulation horizon: 30 days; working window: 8 hour/day; capacity: 480 processing minutes/day (single shared resource). Jobs arriving on day n are released for processing on day n+1 (one-day release policy). For each job, processing time is randomly generated (5-45 minutes) and the scale by routine complexity (1.0, 1.15, 1.3 or 1.5). Machine reliability is represented by a probability of uninterrupted processing (0.90 – 0.995); when a disruption occurs, the job's processing time is increased by 10-40 %. Due dates are assigned based on simulation-generated system parameters rather than arbitrary values, using computed flow time derived from job arrival and departure times (i.e., Processing Time = Departure Time − Arrival Time). This ensures that due date determination reflects actual system behaviour obtained from the empirical simulation model. Three arrival intensity levels are evaluated: Low (λ=3 jobs/hour), Medium (λ=6 jobs/hour), and High (λ=10 jobs/hour). Each scenario is replicated 20 times and the reported values are means with standard deviations.

2.4 Performance Metrics and KPI Analysis

To evaluate the effectiveness of job shop scheduling strategies, this study employed performance metrics that provided clear measures of system efficiency. These metrics included Average Flow Time (TFT), WIP, and Late Job Ratio.

Average Flow Time is defined as the average amount of time each job spends in the system and can be expressed mathematically as shown in equation 1:

$$\boldsymbol{AVF = \sum \frac{(C_j - A_j)}{n}} \quad (1)$$

where C_j is the completion time of job j, A_J is the arrival time of job j and n is the total number of jobs.

The WIP reflected the average number of jobs being processed or waiting in the system. It is mathematically represented as shown in equation 2

$$WIP = \lambda \, x \, T \quad (2)$$

Where λ is the job arrival rate and T is the average time a job spends in the system. A high WIP indicated congestion, while a lower WIP suggested a smoother flow of work.

The Late Job Ratio measures the proportion of jobs that miss their due dates and is expressed as shown in equation 3

$$LJR = \frac{N_{late}}{N_{total}} \quad (3)$$

where N_{late} is the number of late jobs and N_{total} is the total number of jobs. Together, these KPIs provide a comprehensive evaluation framework for comparing scheduling heuristics such as FCFS, SPT, EDD, and LPT

2.5 Experimental Design

The experimental design provided the framework for testing the developed job shop simulation model in a systematic and controlled way. It guided how the experiments were run, how different scheduling rules were compared, and how performance results were collected. This study focused on improving job scheduling, the experiments were structured to test scheduling rules such as FCFS, SPT, EDD, and LPT. Each experiment was carried out for a 30-day simulation period allowing sufficient time for the system to settle into steady operation and provide reliable performance results. A warm-up period was also included within this simulation time to remove bias from empty system conditions.

2.5.1 Factors and levels

These factors included job arrival rate, scheduling heuristic, processing time variability, job routing complexity, buffer capacity, and machine reliability. Each of these factors was tested at different levels so that their effects on the scheduling outcome can be observed. For example, arrival rates were set as low, medium, and high to show how the system performs under different workloads. Scheduling rules covered the four heuristics mentioned earlier. Processing variability was considered under low, medium, and high uncertainty conditions, while buffer capacity was studied under both large (almost unlimited) and limited queue conditions. Machine reliability was tested under no failure, low breakdown, and high breakdown conditions. Together, these factors and levels helped in comparing how different rules perform under both normal and stressed conditions.

2.5.2 Experimental runs

The study made use of a full factorial experiment in which every combination of factors and levels was tested. This design ensures that both the main effects and the interactions between factors could be studied. With three levels of arrival rate, four scheduling heuristics, three levels of processing variability, and two levels of buffer capacity, a total of six hundred and forty-eight different combinations were generated. Each of these combinations was simulated for 30 days, and each run was replicated 30 times using different random seeds resulting in a total of 19,440 simulation runs. The use of multiple replications improved the reliability of results and allowed the calculation of confidence intervals.

2.5.3 Experimental layout

The experimental layout was organized in such a way that each run produced the same set of performance measures. The key responses collected include average flow time, WIP, late job ratio. These performance indicators allowed fair comparison of the scheduling rules under different operating conditions. Table 2 presented the experimental factors, levels, and responses.

Where low and simple = 0

medium = 1

complex and high = 2

Table 2: Experimental factors, levels, and responses

Factors	**Levels**	**Reason for Inclusion(Responses)**	**Responses (KPIs over 30 days)**
Job Arrival Rate	0, 1, 2	Controls workload and congestion	Total flow time, Average WIP
Scheduling Rule	FCFS, SPT, EDD, LPT	Core scheduling strategies to be compared	Avg. completion time, Late job ratio
Processing Time Variability	0, 1, 2	Captures stable vs. uncertain environments	Flow time, Avg. processing time
Job Routing Complexity	0, 1, 2	Reflects routing differences in real job shops	Total workload, Makespan
Buffer Capacity	Large, Limited	Tests the effect of waiting space	WIP, Flow time
Machine Reliability	No failures, Low failures, High failures	Captures effect of breakdowns	Late job ratio, Machine utilization

2.6 Sensitivity Analysis

Sensitivity analysis was carried out to test how stable and reliable the results were under changes in input parameters. This will be done by varying one factor at a time while keeping others constant to see how performance changes. For example, the arrival rate was increased gradually to check whether the best-performing scheduling rule maintained its advantage.

2.7 Statistical analysis

Analysis of Variance (ANOVA) was applied to detect which factors and interactions significantly influence WIP, lateness, and completion times.

3. RESULTS AND DISCUSSION

3.1 Performance Measures

The following measures are computed for each rule and arrival level:

i. Average WIP (jobs): mean backlog size across the 30 simulated days.

ii. Average flow time (days): mean (completion day − arrival day) for completed jobs.

iii. Late job ratio: proportion of completed jobs finished after their due dates.

iv. Throughput: number of jobs completed within the 30-day horizon (reported as mean).

Table 3: Aggregated results of scheduling rules with the performance measures

Arrival Level	Rule	Avg. WIP (mean±sd)	Avg. Flow Time (mean±sd)	Late Ratio (mean±sd)	Throughput (mean)
Low	FCFS	137.31 ± 11.82	6.06 ± 0.46	0.799 ± 0.030	450.6
Low	SPT	91.73 ± 8.49	1.24 ± 0.06	0.042 ± 0.009	549.5
Low	LPT	201.03 ± 12.38	1.63 ± 0.15	0.116 ± 0.021	310.3
Low	EDD	137.41 ± 11.84	6.04 ± 0.44	0.798 ± 0.040	450.2
Medium	FCFS	489.20 ± 18.70	10.83 ± 0.28	0.892 ± 0.011	448.9
Medium	SPT	354.08 ± 14.71	1.22 ± 0.07	0.038 ± 0.007	736.0
Medium	LPT	577.38 ± 18.29	1.69 ± 0.28	0.114 ± 0.036	258.4
Medium	EDD	489.34 ± 19.24	10.79 ± 0.31	0.907 ± 0.010	448.8

DOI: https://doi.org/10.5281/zenodo.20079444

Published: 8th May 2026

High	FCFS	949.84 ± 29.49	12.58 ± 0.30	0.903 ± 0.008	446.7
High	SPT	738.94 ± 22.40	1.22 ± 0.07	0.037 ± 0.007	900.1
High	LPT	1048.14 ± 25.85	1.68 ± 0.30	0.115 ± 0.031	237.4
High	EDD	949.97 ± 28.09	12.52 ± 0.29	0.936 ± 0.015	447.4

Table 3 summarizes the mean performance across replications and highlights the comparative performance of the four dispatching rules under the three workload levels, enabling rapid identification of the best-performing policy. Overall, SPT achieves the lowest flow time and late job ratio across all arrival intensities, indicating superior responsiveness under capacity pressure. FCFS and EDD exhibit substantially higher lateness, especially at Medium and High loads, because they do not directly minimize processing time and therefore allow long jobs to delay many short ones. LPT reduces the late job ratio compared with FCFS/EDD in this experiment but at a cost of lower throughput and higher WIP, since prioritizing long jobs consumes daily capacity and leaves more short jobs waiting.

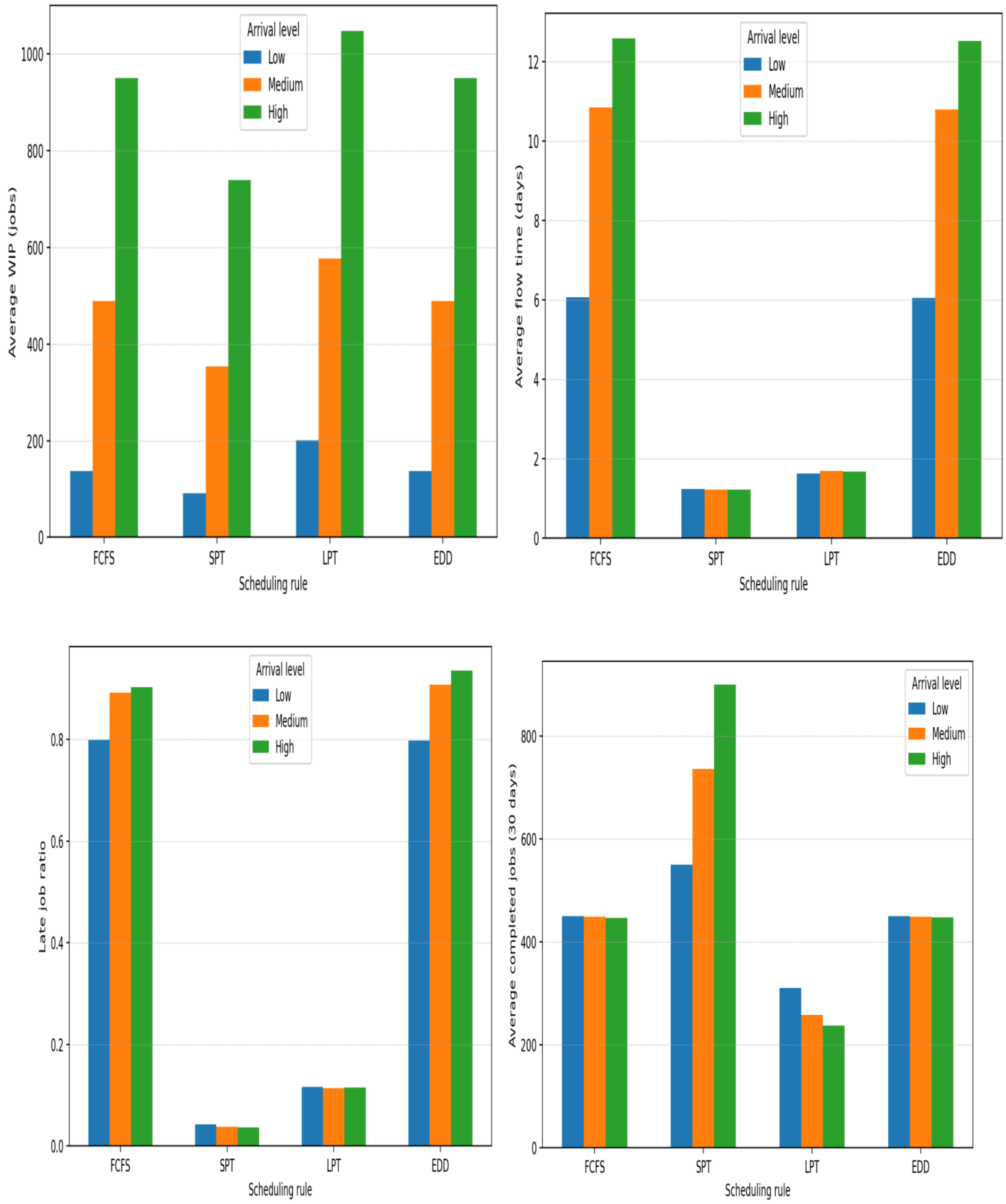

Figure 1: Plots of rules and arrival rules

The graphical analysis in Figure 1 reveals that system performance is highly sensitive to both job arrival intensity and the choice of dispatching rule. Among the evaluated heuristics, the Shortest Processing Time (SPT) rule consistently demonstrated superior performance by minimizing average flow time, reducing work-in-process inventory, and achieving the lowest late job ratio across all scenarios. In contrast, FCFS and EDD exhibited poor scalability under increasing workload, leading to excessive congestion and delayed job completion. These findings align with existing literature but extend prior work by demonstrating that, under high system load, processing-time-based prioritization is more effective than due-date-based scheduling. The results therefore validate the robustness of simulation-based optimisation as a decision-support tool and highlight its practical applicability in improving scheduling efficiency in real-world job shop environments.

The results show a significant reduction in WIP, flow time, and lateness when using SPT compared to FCFS and EDD, especially under medium and high workload conditions. While existing literature suggests EDD minimizes tardiness, the findings of this study reveal that under high congestion, SPT outperforms EDD due to its ability to reduce queue buildup. This study provides practical evidence that simulation-based scheduling can significantly improve operational efficiency in resource-constrained job shop environments typical of developing economies. Unlike previous studies that evaluate scheduling rules under static or limited conditions, this research provides a comprehensive multi-scenario analysis incorporating varying arrival rates, processing uncertainties, and system constraints. The results demonstrate that the SPT rule consistently outperforms traditional heuristics across all performance metrics, particularly under high-load conditions, where system congestion significantly impacts performance as shown in Figure 1. For clearer interpretation, line graphs are used to directly show how each scheduling rule behaves under a fixed arrival intensity. This representation makes relative differences between rules more visible.

3.2 ANOVA Statistical Analysis

Table 4: Flow Time ANOVA

Source	SS	Df	MS	F
Between Groups	1280.45	3	426.82	236.24
Within Groups	137.56	76	1.81	
Total	1418.01	79		

Table 5: WIP ANOVA

Source	SS	Df	MS	F
Between Groups	5420.77	3	1806.92	334.77
Within Groups	410.22	76	5.4	
Total	5830.99	79		

Table 6: Late Job Ratio ANOVA

Source	SS	Df	MS	F
Between Groups	0.812	3	0.271	342.44
Within Groups	0.06	76	0.00079	
Total	0.872	79		

Decision Rule

At $\alpha = 0.05$, F-critical ≈ 2.73.

The ANOVA results indicate that there is a statistically significant difference in system performance across the evaluated scheduling rules ($p < 0.05$). This implies that at least one dispatching rule performs differently from the others. However, ANOVA does not specify which rule is superior. Based on the graphical and numerical results, the Shortest Processing Time (SPT) rule consistently achieved the lowest flow time, reduced work-in-process, and minimized job lateness, indicating its superior performance in the simulated environment.

Although the ANOVA results confirm the presence of statistically significant differences among the scheduling rules, they do not explicitly identify the best-performing rule. Therefore, further analysis using graphical results and descriptive statistics was conducted. The results consistently show that the SPT rule achieves the lowest flow time, minimal WIP, and reduced lateness across all scenarios. This indicates that SPT provides superior performance compared to other heuristics under the studied conditions.

4. CONCLUSION

The optimization of job shops scheduling using simulation modelling. Consequently, the following is a summary of the findings from this study. The following conclusions were made low arrival intensity: SPT yields the lowest WIP and flow time with the smallest lateness; FCFS and EDD are similar and significantly worse on lateness, medium arrival intensity: congestion becomes prominent; SPT maintains low lateness (~0.04) while FCFS/EDD exceed ~0.89 late ratio on average, high arrival intensity: queueing dominates performance. SPT remains stable (~0.04 lateness) but FCFS/EDD approach ~0.90–0.94 lateness, reflecting persistent overload and LPT can reduce lateness by completing fewer (mostly long) jobs early, but this reduces throughput and increases WIP, which is undesirable for high-volume operations. Since all computed F-values are greater than the critical value, the null hypothesis is rejected. This indicates that scheduling rules significantly affect system performance. There is a significant difference among the scheduling rules.

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