Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

ASSESSING SCHEDULING STRATEGIES FOR A SHARED RESOURCE FOR MULTIPLE SYNCHRONOUS LINES

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ABSTRACT

This study uses discrete-event simulation to explore scheduling policies for a shared resource across three synchronous manufacturing lines. The objective is to enhance operational efficiency and reduce blocking and starving downtime. Scheduling for synchronous environments is a less explored area compared to asynchronous systems. Simulation experiments compare the performance of five easy-to-implement scheduling strategies: First-In-First-Out (FIFO), Upstream Priority, Downstream Priority, Random Selection, and Round Robin. The Round-Robin method is commonly used in CPU and computer network scheduling. Scenarios include random station breakdowns. Statistical analysis identifies FIFO and Round Robin strategies as notably effective. Such an offline study could be used to set policies for a digital twin model to determine real-time decisions based on system state, potentially updating the policies using reinforcement learning based on resulting actual performance.

1 INTRODUCTION

Manufacturing and service facilities sometimes must share resources among production lines or service streams due to space unavailability and cost constraints, as multiple instances of equipment, tools, and specialized staff can be prohibitively expensive. The objective of this study is to explore simple methods to schedule common resources when there are overlapping requests, in order to maximize throughput. The interest here is in multiple parallel unpaced synchronized systems (with different flow rates) that do not allow buffers. Such systems have received little attention in the literature.

This research assesses the impact of five distinct scheduling policies under different operational conditions, using a simulation model based on an actual manufacturing process. Using Discrete Event Simulation (DES), the study tests these policies in an environment where equipment failures and repair times are modeled, to determine their effectiveness in improving manufacturing efficiency and flexibility.

2 RELATED WORK

Synchronously paced lines aim for maximum efficiency by synchronizing station activities and eliminating buffers through a pace based on takt time, aligning production with customer demand. This approach ensures continuous material flow and balances production efficiency with operational flexibility. Conversely, asynchronous lines, characterized by variability in processing times, require buffers, presenting different scheduling challenges (Tan and Karabati 2000). Dynamic scheduling for asynchronous lines with buffers has received much attention. For example, Vieira et al. (2003) propose a framework of rescheduling strategies in manufacturing systems, emphasizing adaptability in response to disruptions, applicable to both synchronous and asynchronous environments.

Simulation's importance in manufacturing is highlighted by Law (2014), laying groundwork for DES applications in assessing manufacturing efficiencies. The concept of digital twins, extending beyond traditional simulation approaches, integrates physical and virtual entities, data layers, and user interfaces, evolving in real-time alongside its physical counterpart. This innovation, significantly impacting productivity and decision-making, is demonstrated by Dehghanimohammadabadi et al. (2021). Further emphasized by the autonomous functions of digital twins as explored by Zhou et al. (2020), integrating knowledge-based systems for predictive and optimization capabilities. Its application extends across manufacturing operations planning and scheduling, as shown by Castillo and Smith (2002), among others. Zanchettin (2022) presents an advanced approach to managing production in high-mix human-robot collaborative environments. The paper addresses the challenge of maintaining efficient production despite high variability in job processing times and customer demands using a dynamic scheduling and dispatching algorithm that leverages digital twins and predictive analytics to optimize task allocation and sequencing in real-time. Similarly, Lin et al. (2019) proposes a simulation-based optimization approach integrating several decision-making tools to handle dynamic scheduling complexities. The composite dispatching rule adapts to varying conditions, improving scheduling efficiency by combining multiple traditional dispatching rules. Key methodologies include discrete event simulation and multi-response optimization to ensure robust performance across different scenarios.

In digital twin applications, the digital twin replicates the real system state and recommends actions based on simulating future alternatives, or when speed is critical, through a rule- and perhaps state-based recommender system determined from offline simulations (Biller et al. 2023). Nasiri et al. (2017) also extensively uses digital twins, introducing a composite dispatching rule for real-time scheduling in an open shop environment with stochastic job arrival and processing times. This approach integrates discrete event simulation with multi-layer perceptron artificial neural networks, radial basis function networks, and data envelopment analysis to optimize the dispatching rule, aiming to minimize the mean waiting time of jobs by dynamically selecting the most efficient dispatching rule for each machine. Recent work by Cao (2024) explores real-time scheduling of a maintenance/repair crew in response to multiple competing machine breakdowns using Multi-Fidelity Simulation Optimization (MFSO). A simulation metamodel predicts throughput based on aggregated state space measures and simple scheduling rules, providing results nearly as effective as those based on full simulations, and at a speed allowing real-time decisions.

Despite extensive documentation on asynchronous lines, the literature reveals a gap in addressing shared resource scheduling within synchronous environments, where strict synchronization and consistent takt times complicate resource allocation. Exceptions are Ronen and Starr (1990), who developed policies and models optimizing resource allocation by predicting bottlenecks and adjusting schedules dynamically, and the study reported here, focusing on strategic scheduling of shared resources in multi-line synchronous manufacturing environments. Synchronous environments may be strictly paced, with jobs moving to the next station at the pace time whether the work is complete or not, or unpaced, where a delay in job processing at one station blocks upstream stations and starves downstream stations. Our focus is on unpaced synchronous lines.

3 METHODOLOGY

This study uses DES to analyze three parallel synchronized manufacturing lines based on a large vehicle manufacturing operation. The lines are denoted as A, B, and C. These lines are differentiated by their number of workstations and takt times(see Table 1), which dictate the synchronized pace of work necessary to meet customer demand without the need for intermediate buffers. These workstations are far away from each other in each of the line. The lines are not strictly paced lines: exceeding the pace time (based on takt time) results in starving the downstream station and blocking the upstream station.

Central to the research is a shared crane resource, utilized across workstations within each line under two primary scenarios: a continuous presence throughout a task's duration, or an intermittent presence at the task's start and end. The differential use of the crane under the intermittent scenario is calculated using equations (1) and (2). Actual times for use at the beginning and end the task use random values in this range. The lower and upper bounds are used so that a random value within this range can be selected. This ensures the crane's use varies for each workstation instead of being fixed.

Table 1: Line structure.

Line Name	No. of workstations	Takt Time
A	11	2
B	22	1.5
C	9	5

$$\text{Intermittent Minimum Resource Usage Time(Lower Bound)} = \frac{\text{Takt Time} - \text{Processing Time}}{4} \tag{1}$$

$$\text{Intermittent Maximum Resource Usage Time(Upper Bound)} = \frac{\text{Takt Time} - \text{Processing Time}}{2} \tag{2}$$

This approach provides a framework to evaluate real-world operational efficiencies against crane availability and transit times. Figure 1 shows the crane usage pattern for continuous and intermittent cases.

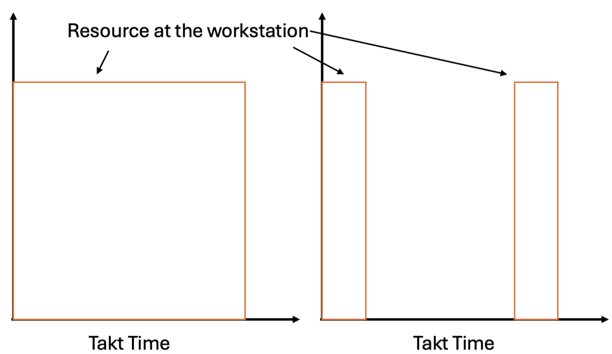

Figure 1: Comparison of crane usage scenarios: on the left, the resource is available throughout the takt time; on the right, the resource is available intermittently.

3.1 Scheduling Policies

Five scheduling strategies under conditions of station failure were considered, with each strategy evaluated against both intermittent and continuous crane usage scenarios.

- **First-In, First-Out (FIFO)** processes workstations based on their arrival order.
- **Upstream Scheduling** emphasizes workstations at the start of the production cycle, formulated as

  $$U = \frac{u_i}{n_i}$$

  where u_i denotes the task number and n_i the total number of workstations. A smaller score is given more priority in upstream scheduling.
- **Downstream Scheduling** focuses on workstations nearing the end of the production cycle, utilizing a similar scoring mechanism as Upstream. A larger score is given more priority in this strategy.
- **Random Scheduling** allocates the crane to workstations without a predefined sequence.
- **Round Robin** distributes crane time equally among workstations in a cyclic manner, ensuring fair resource allocation. This policy is sometimes used in a computer setting as done by Rajput and Gupta (2012). This policy takes into account different time slots for each process in a cyclic order, ensuring equitable access to each resource instead of giving higher priority to a specific line.

3.2 Simulation Model

The DES model of the manufacturing facility is in Simio software (Houck and Whitehead 2019; Kelton et al. 2013), using server blocks to represent workstations and worker entities to model the shared crane resource. This approach allows for an exploration of manufacturing efficiency under various scheduling strategies. The simulated period was 630 days to allow sufficient shifts in relative pace positions across the three lines. Time between station breakdowns was modeled by an exponential distribution with mean 100 hours, and downtime (repair time, in minutes) is governed by a triangular distribution between 30 and 90 minutes with mode 60 minutes. The study's simulation model configurations are summarized in Table 2.

Table 2: Model configurations.

Model No.	Scheduling Strategy	Setting
1	FIFO	Station Failure, Resource needed throughout the task
2	UPSTREAM	Station Failure, Resource needed throughout the task
3	DOWNSTREAM	Station Failure, Resource needed throughout the task
4	ROUND ROBIN	Station Failure, Resource needed throughout the task
5	RANDOM	Station Failure, Resource needed throughout the task
6	FIFO	Station Failure, Resource needed at the start and end of task
7	UPSTREAM	Station Failure, Resource needed at the start and end of task
8	DOWNSTREAM	Station Failure, Resource needed at the start and end of task
9	ROUND ROBIN	Station Failure, Resource needed at the start and end of task
10	RANDOM	Station Failure, Resource needed at the start and end of task

3.2.1 Important Assumptions and Note:

Assumptions & Note:

- Data collection is structured around a 30-day cycle, focusing on the throughput of each production line over each 30-day period (excluding the first).
- The models are running under a 3-shift system with no shift off time.
- No constraint is put on the availability of other resources required for the workstations.
- Line A required the crane resource for 8 workstations out of 11 of the total workstations; Line B needs it for 20 workstations out of 22 of the total workstations; and Line C requires it for 4 workstations out of 9 of the total workstations. Differences in usage will affect differences in performance of each line.

Other assumptions are required for operation of the system. In the event of a station breakdown while using a resource, the resource is released and will return to process the station once it has been repaired. If a station requests a resource but breaks down before the request is processed, the resource will not be dispatched to that station until it is repaired. The intervals between failures and repair times are randomized, introducing variability in operational efficiency.

3.3 Data Collection and Analysis

The objective is to identify statistically significant differences in line throughput under each scheduling strategy, taking into account the variability introduced by station failures and the dynamic use of the crane resource.Analysis included the Kruskal-Wallis test followed by Dunn's test for post-hoc analysis (Dinno 2015). This methodology facilitates an evaluation of the impact of different scheduling strategies on manufacturing line efficiency.

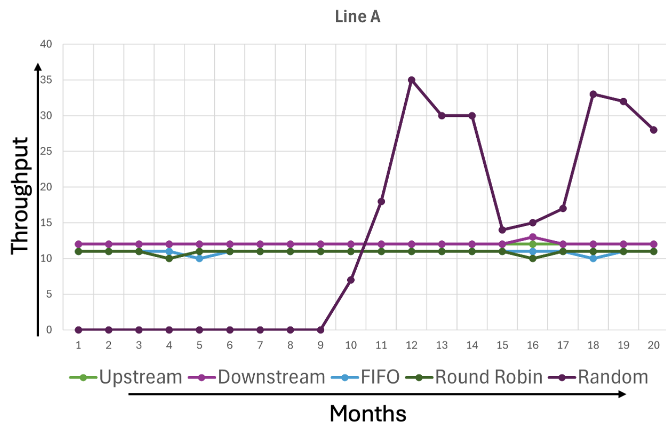

Figure 2: Line A throughput by policy (recorded every 30 days).

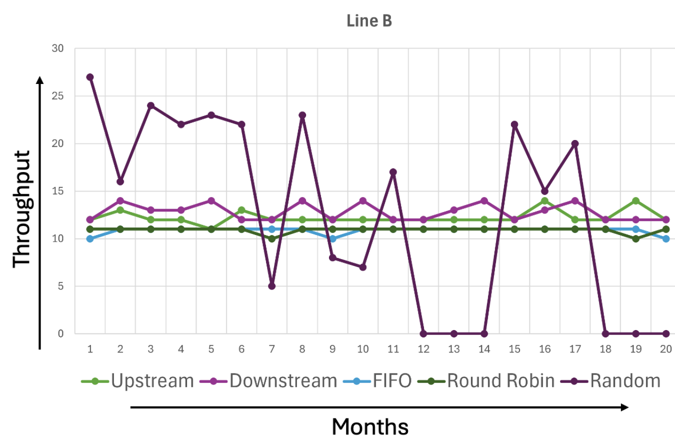

Figure 3: Line B throughput by policy (recorded every 30 days).

4 RESULTS

This section discusses the outcomes of the statistical analysis conducted in R. The analysis considers two scenarios: with and without station failures, and discusses the impact under two resource allocation conditions: continuous presence throughout the task and intermittent presence at the task's initiation and conclusion. The results are derived by taking the median of 4 simulation runs. The median was chosen because taking the average would normalize the Random policy.

4.1 Scenario 1: Station Failures with Continuous Resource Allocation

This scenario introduces random station failures and repair time when the resource is present throughout the task duration. The performance of each line is evaluated under all scheduling strategies, providing insights into the resilience and efficiency of these policies amidst station failures and repair time. The throughput patterns observed across lines A, B, and C under each policy are depicted in Figures 2, 3, and 4. These figures show the performance of each policy over time, highlighting the variability vs. consistency inherent to each strategy. All policies produce consistent results over time except for the random policy, which shows unpredictable throughput over time.

For example for line A, an initial output of zero followed by an upward trend is seen in the Random policy after the 9th period due to a higher but random selected priority given to line B and C over Line

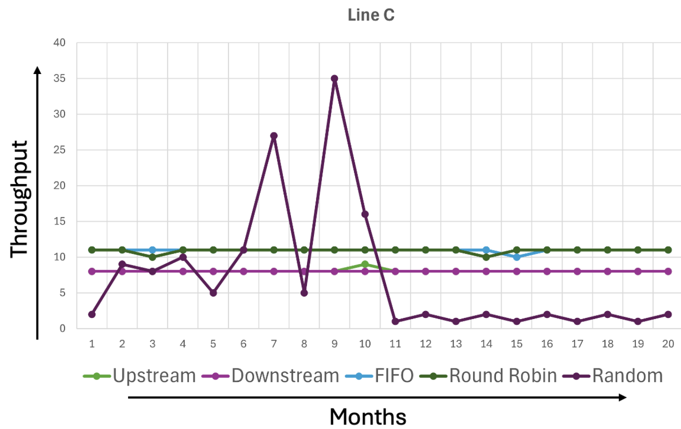

Figure 4: Line C throughput by policy (recorded every 30 days).

A during that period of time. A similar behaviour is seen from the 11th time period of line C where the throughput is zero because a random but higher priority is given to line A and B. This unpredictable behavior is a distinct disadvantage for the Random policy. For lines A and B, the the Upstream and Downstream policies are indistinguishable, with consistent, slightly higher throughput than Round Robin and FIFO policies. But for Line C, Round Robin and FIFO show consistently higher throughput. These results suggest a distinct performance edge for FIFO and Round Robin for line C, but Upstream and Downstream were superior for Lines A and B.

For line A, the Random policy shows a high degree of variability and less predictability in performance with a standard deviation of 10.19 and coefficient of variation of 81. In contrast, the FIFO, Round Robin, Upstream, and Downstream policies exhibit a more consistent and controlled utilization pattern with standard deviation of 0.73, 0.89,0.31 and 0.31 respectively and mean of 12,12,10 and 10. A consistency can be seen when compared to other scenarios that for line A Upstream and Downstream perform well as compared to the other policies. Line B reveals a similar trend where the Random policy stands out with greater variability with a deviation of 9.44, as denoted by the more substantial spread in the data. The other policies maintain a tighter performance band, suggesting more stable resource utilization over time with mean of 8,8,10 and 10. For line C, the throughput for the Random policy once again indicates higher variability. Also the median is a low value, as after the 9th period there was no throughput recorded for line C. Amongst the other strategies FIFO and Round Robin perform well with a mean of 10.9.

4.1.1 Nature of Data for Scenario 1

In some cases the data have identical values across multiple 30-day periods. This occurs when there is no blocking or starving because the lines are synchronous. Identical values of zero throughput over multiple 30-day periods can occur when there is long-term blocking based on priorities assigned by particular scheduling policies. These throughput distributions disallow the use of parametric methods like ANOVA that assume normality. It was necessary to use non-parametric methods that do not require the assumption of normal distribution. The Kruskal-Wallis test followed by Dunn's test (Dinno 2015) were used to evaluate the statistical differences across various scheduling policies.

4.1.2 Statistical Analysis for Scenario 1

A nonparametric ANOVA was conducted based on the Kruskal Wallis Test (Montgomery 2020). The results from the Kruskal-Wallis test indicated statistically significant differences in performance between at least two policies for each line, as all p-values are below the 0.05 threshold. Using the ad-hoc analysis as performed in the previous scenarios, the Dunn's test was run (Dinno 2015). Subsequently, Dunn's test

Table 3: Summary of all significant pairwise comparisons with adjusted p-values for Scenario 1.

Line	Policy 1	Policy 2	Adjusted p-value	Significant at $\alpha = 0.0025$
A	Downstream	FIFO	1.500600e-05	Yes
A	Downstream	Round Robin	1.500600e-05	Yes
A	Downstream	Upstream	2.614164e-05	Yes
A	Round Robin	Upstream	2.614164e-05	Yes
B	Downstream	FIFO	2.265216e-05	Yes
B	Downstream	Random	4.321582e-05	Yes
B	Downstream	Upstream	3.544843e-05	Yes
B	Downstream	Round Robin	3.946249e-05	Yes
B	FIFO	Random	2.046488e-04	Yes
B	Random	Round Robin	2.947633e-04	Yes
B	Random	Upstream	5.260836e-05	Yes
B	Round Robin	Upstream	6.110067e-05	Yes
C	Downstream	FIFO	1.641764e-06	Yes
C	Downstream	Round Robin	3.107639e-06	Yes
C	Downstream	Upstream	3.107639e-06	Yes
C	FIFO	Random	2.614506e-07	Yes
C	Random	Round Robin	5.150112e-07	Yes
C	Round Robin	Upstream	5.798284e-06	Yes

provided further insights into which specific policy comparisons stood out with statistically significant differences.

The results from Table 3 from Dunn's test highlight that for Line A, the FIFO and Round Robin policies differ substantially from each other. While Upstream and Downstream do not differ statistically from each other for line A, but differ from all the other strategies. For Line B, all the policies differ from each other. Downstream showed a higher output than Upstream, this is reason why these policies show a statistical difference as well. On Line C, upstream and downstream don't vary and FIFO and Round Robin also don't vary from each other.

4.2 Scenario 2: Station Failures with Resource Needed At the Beginning and End of the Task

This scenario allocates the crane to a workstation at the start and end of processing at that workstation, with intermittent time periods determined by (1) and (2) in Section 3. For the interim period, the crane can be reassigned to another workstation on the same line, or a workstation on a different line.

Similar to the previous scenario, the performance of the policies for the different lines were evaluated. The throughput patterns observed across lines A, B, and C under each policy are depicted in Figures 5, 6, and 7.

Figure 5 shows a variable pattern for the Random Scheduling policy output of line A with a deviation of 7. The other scheduling policies show more consistent performance. This behavior is similar to that for line A in scenario 1, where all other policies performed consistently well, the average mean is 31,31, 28 and 28. For line B, 6 Upstream and Downstream perform significantly well with a mean of 22. In contrast, line C (Figure 7) displays different results: Round Robin and FIFO are more effective than the Upstream and Downstream with a mean of 28 and CV of 1.6 and 1.5. This difference also occurred in Scenario 1. When comparing the performance of the Random policy for the three lines, it can be observed that Line A has better performance than line B, there is no apparent reason for this other than that the random allocation of the crane to line A was given more preference throughout the simulation runtime than line B.

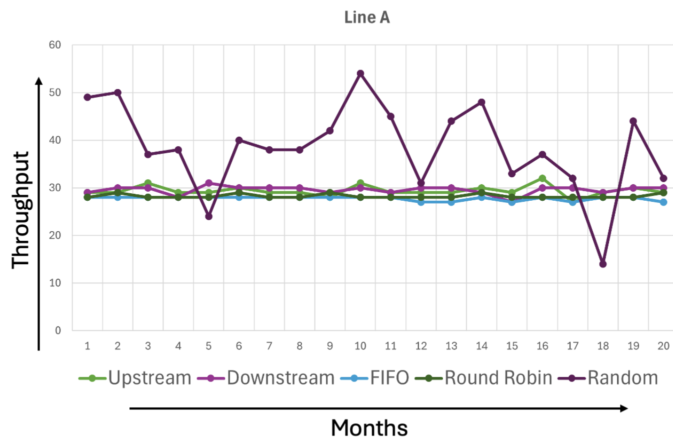

Figure 5: Line A throughput by policy (recorded every 30 days).

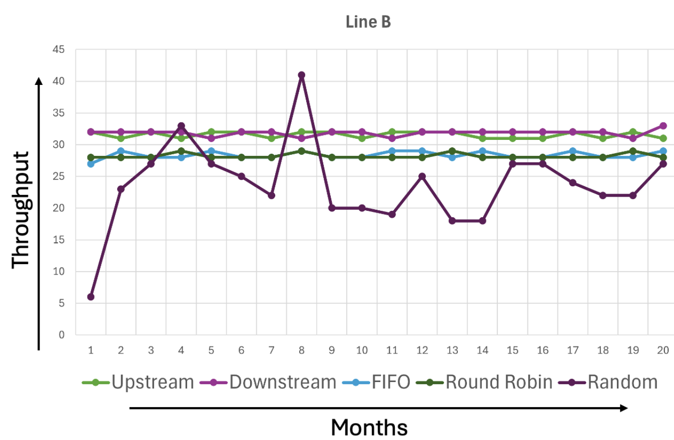

Figure 6: Line B throughput by policy (recorded every 30 days).

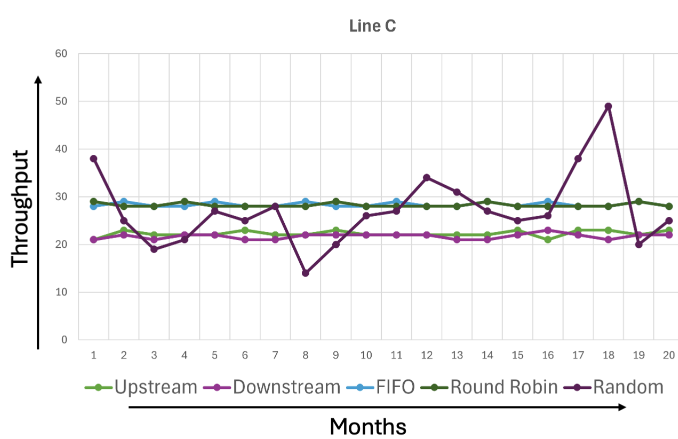

Figure 7: Line C throughput by policy (recorded every 30 days).

4.2.1 Nature of Data for Scenario 2

As for Scenario 1, results indicated clear departure from normal distribution so Kruskal Wallis and Dunn's Test were used to compare the performance of the different policies. The deviation from normality was found by using QQ plots which showed that the data points deviate from the tails. For all policies except the Random policy, the throughput results had very small variation except for a few outliers.

4.2.2 Statistical Analysis for Scenario 2

The Kruskal Wallis and Dunn's Test the identified statistically significant pairwise policy performance differences. It was found that, for line A, Downstream policy was significantly different from FIFO and Random policies. FIFO was significantly different from Random and Round Robin policies. The Random policy showed a significant difference when compared to Round Robin and Upstream policies. Downstream and Upstream policies did not demonstrate a significant difference between each other. Similarly for line B the Downstream policy was significantly different from all other policies. FIFO showed a significant difference when compared to Random and Upstream policies. The Random policy was significantly different from Round Robin and Upstream policies. Downstream and Upstream policies did not show a significant difference between each other. And for line C the Downstream policy was significantly different from all other policies except for Round Robin. FIFO was significantly different from Random and Upstream policies. The Random policy showed a significant difference when compared to Round Robin and Upstream policies.

As for Scenario 1, these results show that the scheduling policy choice has a considerable impact on performance across different lines, but no single policy is universally the best or worst across all lines. These results differ in some aspects from the results of the previous section. Table 4 summaries all the significant pairwise comparisons. In the next section both the scenarios were compared see which policies worked the best in which scenario.

Table 4: Summary of all significant pairwise comparisons with adjusted p-values for Scenario 2.

Line	Policy 1	Policy 2	Adjusted p-value	Significant at $\alpha = 0.0025$
A	Downstream	FIFO	2.748722e-05	Yes
A	Downstream	Round Robin	5.837157e-04	Yes
A	Downstream	Upstream	3.949715e-04	Yes
A	FIFO	Random	2.792400e-11	Yes
A	FIFO	Upstream	1.628251e-04	Yes
A	Random	Round Robin	1.124100e-07	Yes
A	Random	Upstream	4.032920e-04	Yes
B	Downstream	FIFO	2.106122e-05	Yes
B	Downstream	Random	1.473180e-11	Yes
B	Downstream	Round Robin	3.847291e-06	Yes
B	Downstream	Upstream	3.446165e-04	Yes
B	Random	Upstream	1.011359e-09	Yes
B	Round Robin	Upstream	7.720355e-05	Yes
C	Downstream	FIFO	4.189856e-09	Yes
C	Downstream	Random	3.566446e-04	Yes
C	Downstream	Round Robin	1.715482e-08	Yes
C	Downstream	Upstream	1.225233e-06	Yes
C	Random	Upstream	4.040310e-06	Yes

5 DISCUSSION

5.1 Scenario 1: Station Failures with Continuous Resource Allocation

The incorporation of random station failures introduced a stochastic element to the evaluation, aiming to assess the resilience of scheduling policies under more realistic and challenging conditions. The findings are summarized below:

- FIFO and Round Robin: Maintained resilience and efficiency even in the face of station failures. These policies demonstrated an ability to adapt to disruptions, ensuring consistent throughput.
- Random: Its performance remained unpredictable, with high variability especially noted on line A and line C. Thus unpredictability was compounded by the introduction of station failures.
- Downstream and Upstream: Both policies showed varying degrees of robustness against station failures. Downstream particularly stood out in some lines for its ability to adapt to the added complexity of station failures, indicating potential line-specific advantages.

5.2 Scenario 2: Station Failures with Resource Needed At the Beginning and End of the Task

This scenario combined the complexity of station failures with the intermittent resource allocation model. The findings were as follows:

- FIFO and Round Robin: These policies again showed effective performance, particularly on line C, where they were more efficient than the alternatives. Their adaptability to station failures, combined with resource allocation at task boundaries, showcased their potential for maintaining operational efficiency under complex conditions.
- Random: Its performance was notably erratic and unpredictable across all lines. The policy's variable nature was emphasized by the combined effects of station failures and the specific resource allocation model.
- Downstream and Upstream: Demonstrated strong performance, especially on specific lines like line B for Downstream. These policies benefited from the model where resources were needed only at the beginning and end of workstations, showing that their effectiveness could be enhanced under certain operational constraints.

To identify one policy that performed well in all scenarios the average line utilization for each policy across all lines was computed and then overall average utilization for each policy was found across the scenarios. From this analysis it was understood that:

1. Upstream, Downstream, FIFO and Round Robin showed consistent performance across lines when compared to the Random scheduling policy
2. Upstream, Downstream, FIFO and Round Robin showed consistent performance across lines for both continuous and intermittent use scenarios. But requiring the crane only during the start and end of the task and allowing reallocation between leads to higher throughput. The performance of Random scheduling cannot be was erratic for both scenarios.
3. Averaging utilization across all three lines, Round Robin and FIFO showed superior performance, Figure 8, this was due to its better performance for line C for all scenarios and consistently good performance for line A and B. Other strategies showed varying degrees of robustness as in some scenarios. For all scenarios if the consistency and overall throughput is considered then Round Robin is preferred over FIFO.

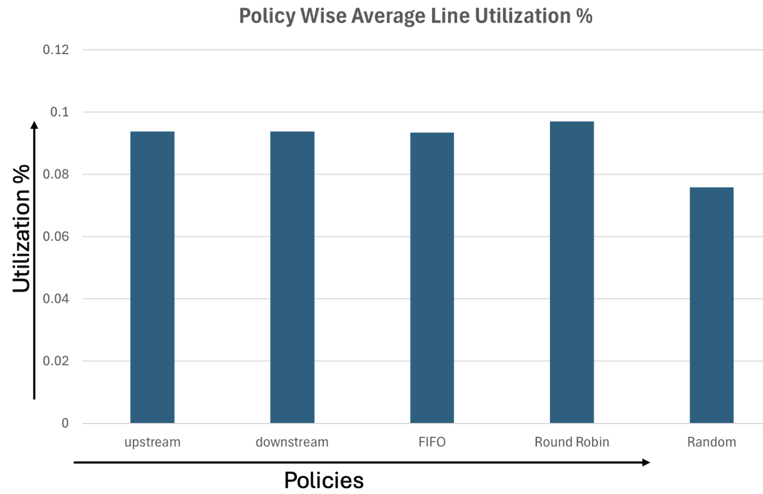

Figure 8: Policy vs. average utilization across scenarios and lines.

6 CONCLUSION

In this study, an exploration into the dynamics of scheduling systems for shared resources within a synchronous manufacturing environment used discrete event simulation. The results identified the effectiveness of the Round Robin scheduling policy when compared with other scheduling policies under various operational scenarios. The analysis showed notable differences in operational efficiency across scenarios and policies.

The findings suggest that the selection of a scheduling policy for a shared resource across multiple synchronous lines should be based on the specific line characteristics and operational objectives of the manufacturing setting. For example, if the aim is to ensure an equitable distribution of resources across all production lines, the Round Robin scheduling strategy emerges as the optimal choice.

The concept of sharing resources, supported by advanced manufacturing technologies, is increasingly common in the industry. In such systems, multiple production lines often share resources, such as labor or machinery, to coordinate cross-organizational resources and provide on-demand services for personalized manufacturing requirements. Examples of its use include the aerospace industry, where tasks such as painting utilize a common overhead gantry crane.

7 FUTURE WORK

Future research aims to extend this study by incorporating more complex manufacturing scenarios, moving beyond the current simplifications to include factors like operator downtime and time-varying pace to meet demand variations. The study could also explore multiple resources to including varied resource allocation strategies such as multiple dispatches to the same station depending on task requirements.

A significant direction for expansion involves leveraging advanced predictive analytics and machine learning to enhance the adaptability of scheduling policies. By analyzing historical data, these technologies could dynamically select the most suitable scheduling strategy based on current production demands across lines, transitioning seamlessly between random, FIFO, LIFO, and Round Robin strategies as the situation warrants. Ultimately, the goal is to evolve the current digital model into a digital twin by integrating real-time data acquisition for a continuous feedback loop between virtual models and their physical counterparts. This development would not only provide a more accurate simulation environment but also enable a detailed comparison between meta-modeling and simulation approaches, fostering a deeper understanding of how to optimize manufacturing efficiency in real time.

ACKNOWLEDGMENTS

Drs. Dennis Pegden and Jeff Smith at Simio and Catherine Harmonosky at Penn State provided important guidance on the simulation aspects of this study. We thank Dr. David Sturrock at Simio for providing access to the Simio software. We also thank the WSC Proceedings editors and reviewers for helping us improve the paper.

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