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# Optimization of Dispatching Desicions in Stochastic Unreliable Flexible Manufacturing Systems using Simulation and the Taguchi Method

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***Abstract* - This paper investigates the optimization of part tardiness in a simulated Flexible Manufacturing System (FMS). A discrete-event simulation model developed in ARENA Rockwell, designed to accurately replicate a stochastic and dynamic production environment. The model represents a complex FMS comprising five distinct part types, each with its own unique process flow, and a shared pool of automated resources, including an Automated Guided Vehicle (AGV) system and multiple processing centers. The aim of this paper is to evaluate the individual and interactive effects of five different queuing disciplines on part tardiness. To achieve this objective efficiently, a Design of Experiments (DOE) framework with a Taguchi method is utilized to plan the simulation runs and minimize the number of experiments required. The data generated from these simulations is collected and analyzed statistically using Minitab software. The analysis focuses on identifying the most influential factors (queuing disciplines) on tardiness, and on finding the optimal and most robust configuration that minimizes both tardiness and its variability through a Signal-to-Noise (S/N) ratio analysis.**

***Keywords - Flexible Manufacturing System, Part Tardiness, Discrete-Event Simulation, Design of Experiments, Taguchi Method, Queueing Disciplines.***

## I. INTRODUCTION

FMS is an integrated system of automated machine tools, automated material handling systems (e.g., AGVs), and a centralized computer control system [1]. The modern manufacturing landscape is defined by its demand for flexibility, efficiency, and rapid response to market changes. In this environment, Flexible Manufacturing Systems (FMS) have emerged as a critical solution, offering a strategic advantage over traditional production lines. An FMS integrates computer-controlled machine tools, such as CNC machines and robots, with a sophisticated material handling system, typically comprising Automated Guided Vehicles (AGVs) and conveyor belts, all coordinated by a central supervisory computer. This integration allows for the efficient production of a diverse range of products in a single system, a capability often referred to as "mid-volume, mid-variety" production. The core strength of an FMS lies in its inherent flexibility, which can be categorized into machine flexibility, routing flexibility, and product flexibility. This adaptability enables a manufacturing facility to quickly reconfigure its production to handle new parts or adjust to fluctuating demand without significant downtime or capital investment.

Research by Alkaff et al. (2020) analyzed different batching strategies in flexible flow shops under stochastic conditions. They concluded that dynamic batch size optimization, where batch sizes adapt based on real-time system states, significantly improves system performance compared to static batching strategies [2]. Studies by Kundakcioglu et al. (2019) show that minimizing setup times between batches and optimizing batch sizes to reduce the impact of machine breakdowns can lead to improved productivity [3]. In research by Chung et al. (2020), Simio discrete event simulation software was employed to model resource allocation strategies in a flexible flow shop with stochastic failures [4]. In another study, Tiwari et al. (2018) examined how batching affects system performance metrics such as cycle time and system utilization in a stochastic flexible flow shop [5]. Kumar et al. (2017) applied Discrete-Event Simulation to model a flexible flow shop with stochastic machine downtimes and random processing times [6]. Zhang et al., (2024) addresses resource allocation challenges in multi-stage batch-processing steel production under stochastic conditions [7].

The choice of a queuing discipline, or dispatching rule, dictates the order in which parts are selected for processing. For example, a First-In, First-Out (FIFO) rule may seem fair but could cause urgent parts to be delayed, while an Earliest Due Date (EDD) rule might prioritize urgent parts but lead to underutilization of resources. The problem this paper addresses is the lack of a systematic and efficient methodology for determining the optimal combination of queuing disciplines to collectively minimize part tardiness in a complex FMS.

The overall paper design is a simulation-based optimization approach. The primary tool is a discrete-event simulation model of a Flexible Manufacturing System (FMS) developed in ARENA Rockwell. This model serves as a controlled experimental environment that allows for the systematic evaluation of different operational scenarios. The experiments are not conducted arbitrarily but are guided by a Design of Experiments (DOE) methodology, specifically the Taguchi method, using Minitab statistical software. This approach efficiently explores the effects of multiple experimental factors represented by selected queues within the system on the response variable, which is part tardiness. Different queuing

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disciplines are assigned as experimental levels at each queue. The simulation runs generate the required performance data, which are then analyzed in Minitab to identify robust queuing configurations that minimize tardiness.

## II. FMS LAYOUT AND COMPONENTS

The system modeled in this paper represents a flexible manufacturing system (FMS) with job shop characteristics. It consists of a single load/unload station, four machine centers, and a single Automated Guided Vehicle (AGV) loop for material handling. The processing stations are equipped with various resources, including machines and robotic arms for material handling tasks. The flow of parts is determined by their assigned part type and routing sequence, as shown in Figure 1. Figure 1 presents a graphical representation of the discrete-event simulation model developed in ARENA. The figure provides a high-level overview of the FMS layout, including the load/unload station, machine centers, AGV network, and the main process flow logic, and illustrates the key modules and resources used in the simulation.

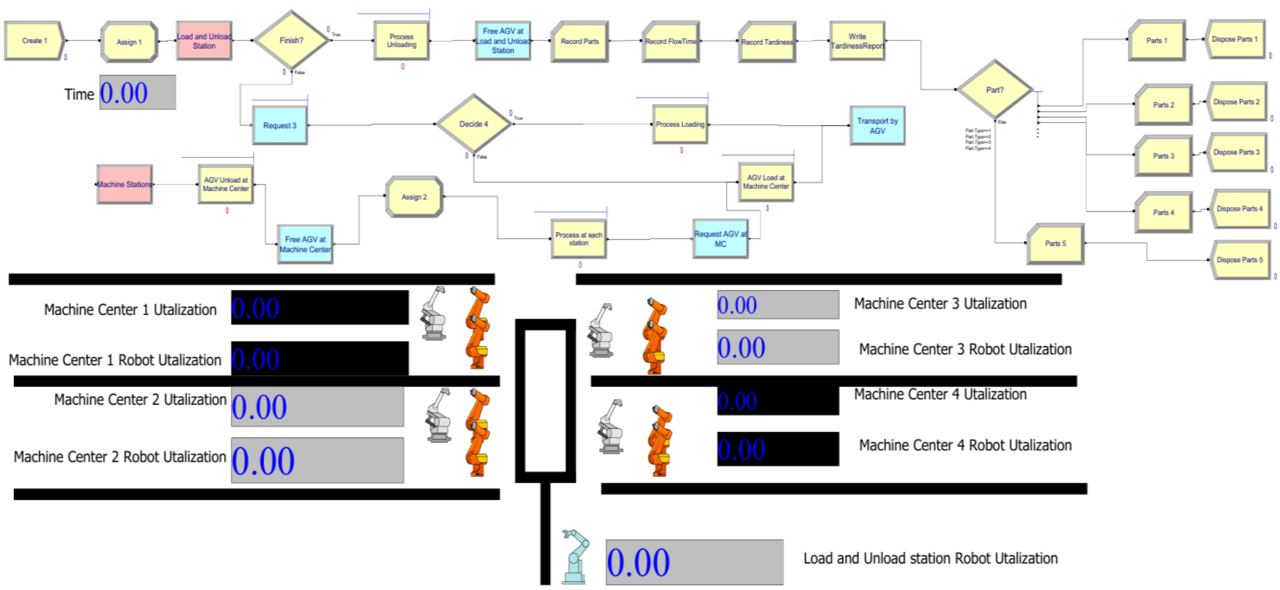


Fig. 1. *Case FMS ARENA Simulation Model*

The system being modeled is a manufacturing or production system that simulates the flow of different types of parts through a series of processes, including loading, processing, and unloading, using automated guided vehicles (AGVs) and robotic resources. The system begins by creating parts at a designated entry point. These parts are assigned specific attributes, such as type, due date, and priority. They are then transported between the load/unload station and multiple machine stations for processing, according to their assigned routing sequences. Material handling is performed using an Automated Guided Vehicle (AGV) system, while loading and unloading operations are carried out by robotic resources. Upon completion of all required processing steps, parts exit the system, and performance measures such as flow time and tardiness are recorded. To evaluate part tardiness, each part is assigned a due date upon creation. Due dates are generated using a probabilistic approach to introduce variability across jobs and reflect heterogeneous delivery requirements. In this paper, due dates are sampled from a normal distribution with a mean of 200 minutes and a standard deviation of 10 minutes. This approach ensures a diverse set of due dates across part types, enabling meaningful evaluation of due-date–based dispatching rules.

The five queuing disciplines under investigation are implemented as experimental factors within the queue modules of the ARENA simulation model. Each queuing discipline represents a different dispatching rule governing job selection at machine queues. For example, a queue can be configured to follow a FIFO (First-In, First-Out) policy or a due-date–based rule such as Earliest Due Date, implemented by prioritizing jobs with lower due-date values. In the experimental design, the alternative queuing disciplines constitute the different levels of each factor, allowing systematic evaluation of their impact on part tardiness across the simulated manufacturing system.

The system uses several queues where parts wait for resources. These queues have different rules for how parts are prioritized:

1. FIFO (First-In, First-Out).
2. LIFO (Last-In, First-Out).
3. Lowest Attribute Value (Part Priority).
4. Lowest Attribute Value (Part Due date).
5. Lowest Attribute Value (Part Cycle time).

There are 15 defined sequences, which are likely assigned to different parts or a different mix of products. Each sequence specifies a path of stations and the process time at each one. For example, Sequence 1 dictates that a part goes from MC3 Station to MC1 Station, then to MC4 Station, then MC2 Station, and finally back to L UL Station.

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### *A. Selection of Factors*

In this paper, the experimental factors correspond to the key queue locations where dispatching decisions are made within the system. These factors are:

1. Process Loading
2. Process Unloading
3. Automated Guided Vehicle Loading
4. Automated Guided Vehicle Unloading
5. Request 3: Advanced Transfer to Process Loading

To reduce the number of required simulation runs while capturing the main effects of the experimental factors, an orthogonal array is selected using Minitab. Given five factors each evaluated at five levels, an L25 orthogonal array is employed, allowing the experimental space to be explored using only 25 unique factor-level combinations.

## III. RESULTS AND DISUSSION

This chapter presents the results of the simulation-based experimental study. It begins with a structured presentation of the aggregated performance results obtained from the Taguchi experimental design, followed by statistical analysis using ANOVA and Signal-to-Noise (S/N) ratios. The findings are used to identify the most effective queueing configurations for minimizing part tardiness. Table I presents the average tardiness results for each experimental run in the orthogonal array. For every run, the reported value represents the mean tardiness across all replications, providing the aggregated performance data used in the subsequent statistical analysis.

TABLE I. AVERAGE PART TARDINESS FOR TAGUCHI ORTHOGONAL ARRAY RUNS

| # | Process Unloading.Queue | Process Loading.Queue | AGV Unload at Machine Center. | AGV Load at Machine Center.Qu | Request Lowest Attribute Value (Part Priority).Queue | Tardiness (Minutes) |
|---|---|---|---|---|---|---|
| 1 | First In First Out | First In First Out | First In First Out | First In First Out | First In First Out | 566.06 |
| 2 | First In First Out | Last In First Out | Last In First Out | Last In First Out | Last In First Out | 414.63 |
| 3 | First In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part Priority) | 274.30 |
| 4 | First In First Out | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part DueDate) | 566.93 |
| 5 | First In First Out | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part CycleTime) | 566.06 |
| 6 | Last In First Out | First In First Out | Last In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part DueDate) | 566.93 |
| 7 | Last In First Out | Last In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part CycleTime) | 566.06 |
| 8 | Last In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part CycleTime) | First In First Out | 566.06 |
| 9 | Last In First Out | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part CycleTime) | First In First Out | Last In First Out | 414.63 |
| 10 | Last In First Out | Lowest Attribute Value (Part CycleTime) | First In First Out | Last In First Out | Lowest Attribute Value (Part Priority) | 274.30 |
| 11 | Lowest Attribute Value (Part Priority) | First In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part CycleTime) | Last In First Out | 414.63 |
| 12 | Lowest Attribute Value (Part Priority) | Last In First Out | Lowest Attribute Value (Part DueDate) | First In First Out | Lowest Attribute Value (Part Priority) | 566.93 |
| 13 | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part CycleTime) | Last In First Out | Lowest Attribute Value (Part DueDate) | 566.93 |
| 14 | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part DueDate) | First In First Out | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part CycleTime) | 566.06 |
| 15 | Lowest Attribute Value (Part Priority) | Lowest Attribute Value (Part CycleTime) | Last In First Out | Lowest Attribute Value (Part DueDate) | First In First Out | 566.06 |
| 16 | Lowest Attribute Value (Part DueDate) | First In First Out | Lowest Attribute Value (Part DueDate) | Last In First Out | Lowest Attribute Value (Part CycleTime) | 566.06 |
| 17 | Lowest Attribute Value (Part DueDate) | Last In First Out | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part Priority) | First In First Out | 566.06 |
| 18 | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part Priority) | First In First Out | Lowest Attribute Value (Part DueDate) | Last In First Out | 414.63 |
| 19 | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part DueDate) | Last In First Out | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part Priority) | 274.30 |
| 20 | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part Priority) | First In First Out | Lowest Attribute Value (Part DueDate) | 566.93 |
| 21 | Lowest Attribute Value (Part CycleTime) | First In First Out | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part Priority) | 274.30 |
| 22 | Lowest Attribute Value (Part | Last In First Out | First In First Out | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part DueDate) | 566.93 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| | CycleTime) | | | | | |
| **23** | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part Priority) | Last In First Out | First In First Out | Lowest Attribute Value (Part CycleTime) | 566.06 |
| **24** | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part Priority) | Last In First Out | First In First Out | 566.06 |
| **25** | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part CycleTime) | Lowest Attribute Value (Part DueDate) | Lowest Attribute Value (Part Priority) | Last In First Out | 414.63 |

### A. *Selection of Factors*

Table II summarizes the mean tardiness values for each level of every experimental factor. These results support the identification of effective queuing-rule configurations for minimizing tardiness under the modeled stochastic environment. In particular, Level 3 of the Request Queue achieves the lowest mean tardiness, confirming it as the most effective configuration under the modeled conditions. This dominance suggests that dispatching decisions at the Request Queue play a critical role in controlling congestion propagation throughout the system.

TABLE II. RESPONSE TABLE FOR TARDINESS MEANS

| **Level** | **Process Unloading.Queue_1** | **Process Loading.Queue_1** | **AGV Unload at Machine Center._1** | **AGV Load at Machine Center.Qu_1** | **Request 3.Queue_1** |
|---|---|---|---|---|---|
| 1 | 477.6 | 477.6 | 477.6 | 536.1 | 566.1 |
| 2 | 477.6 | 536.1 | 477.6 | 477.6 | 414.6 |
| 3 | 536.1 | 477.6 | 477.6 | 477.6 | 332.8 |
| 4 | 477.6 | 477.6 | 536.1 | 477.6 | 566.9 |
| 5 | 477.6 | 477.6 | 477.6 | 477.6 | 566.1 |
| Delta | 58.5 | 58.5 | 58.5 | 58.5 | 234.1 |
| Rank | 4.5 | 2.5 | 2.5 | 4.5 | 1 |

### B. *Main Effects*

Table III shows the ANOVA for the significant factors shows that the Request 3 queue is very significant with a p-value<0.05. The considered factors explain around 95.55% of the part tardiness readings. See table IV.

TABLE III. ANALYSIS OF VARIANCE

| **Source** | **DF** | **Adj SS** | **Adj MS** | **F-Value** | **P-Value** |
|---|---|---|---|---|---|
| Process Unloading.Queue_1 | 4 | 13701 | 3425 | 1.00 | 0.500 |
| Process Loading.Queue_1 | 4 | 13701 | 3425 | 1.00 | 0.500 |
| AGV Unload at Machine Center._1 | 4 | 13701 | 3425 | 1.00 | 0.500 |
| AGV Load at Machine Center.Qu_1 | 4 | 13701 | 3425 | 1.00 | 0.500 |
| Request 3.Queue_1 | 4 | 239352 | 59838 | 17.47 | 0.008 |
| Error | 4 | 13701 | 3425 | | |
| Total | 24 | 307858 | | | |

TABLE IV. MODEL SUMMARY

| **S** | **R-sq** | **R-sq(adj)** | **R-sq(pred)** |
|---|---|---|---|
| 58.526 | 95.55% | 73.30% | 0.00% |

### C. *Identification of Optimal Settings*

The identified optimal configuration consists of Process Unloading at Level 5 (Lowest Attribute: Cycle Time), Process Loading at Level 1 (FIFO), AGV Unload at Level 3 (Lowest Attribute: Priority), AGV Load at Level 5 (Lowest Attribute: Cycle Time), and Request Queue at Level 3 (Lowest Attribute: Priority). The expected mean tardiness under this configuration is approximately 286 minutes. See figure 2.

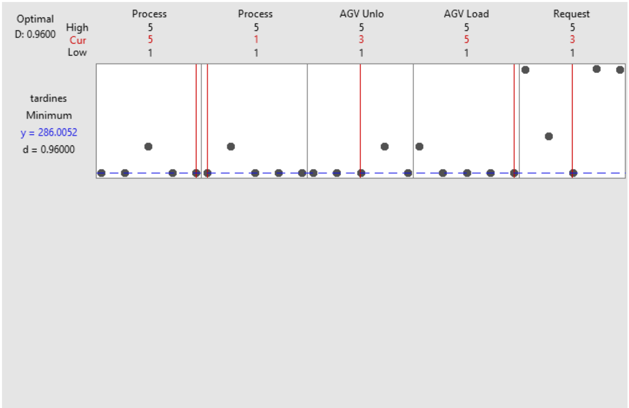


Fig. 2. *Respose Plot of the optimized part Tardiness*

The Response Optimizer (Figure 4.3) predicts an average part tardiness of approximately 286 minutes with a composite desirability of 0.96. A confirmatory simulation run in Arena using the identified optimal settings resulted in an average part tardiness of 274.3 minutes (4.57 hours), validating the effectiveness of the Taguchi-based optimization.

## IV. CONCLOUSIONS

This paper addressed a critical challenge in the management of Flexible Manufacturing Systems (FMS): minimizing part tardiness through effective queue management. A stochastic FMS model was developed in ARENA Rockwell, incorporating five distinct part types, an AGV-based material handling system, and multiple processing stations. To systematically evaluate the impact of different queuing disciplines, a Design of Experiments (DOE) approach specifically the Taguchi method was implemented. Simulation experiments were conducted using an orthogonal array, and the resulting tardiness data were analyzed in Minitab. The analysis combined Analysis of Variance (ANOVA) to identify statistically significant factors with Signal-to-Noise (S/N) ratio analysis to determine the most robust and optimal combination of queuing disciplines.

The ANOVA results demonstrated that the Request Queue was the only statistically significant factor affecting part tardiness. This confirms that decision-making at this stage has a dominant influence on overall system performance and validates the premise that queue management plays a critical

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role in FMS scheduling. The combined use of ARENA simulation and the DOE–Taguchi approach proved to be an effective and efficient framework for FMS optimization. This methodology enabled the structured evaluation of multiple factors with a limited number of simulation runs, providing a robust and data-driven solution. The results provide quantitative evidence on how queuing decisions influence part tardiness in a stochastic FMS environment, highlighting the critical role of dispatching control in overall system performance.

This paper evaluated a selected set of classical dispatching rules as experimental levels. Further research could examine more advanced scheduling ratios, composite, or dynamically switching rules such as critical ratio to expand the decision space.

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## REFERENCES

[1] Stecke, K. E., & Solberg, J. J. (1981). The optimality of unbalanced production lines. International Journal of Production Research, 19(5), 585–599.

[2] Alkaff, S., Zulkifli, N., and Omar, M. (2020). Dynamic Batching in Stochastic Manufacturing Systems. Journal of Manufacturing Systems, 49, 123-130.

[3] Kundakcioglu, S., Tan, M., and Rashid, K. (2019). Minimizing Setup Times in Flexible Flow Shops: A Simulation Approach. European Journal of Operational Research, 275(3), 831-845.

[4] Chung, J., Soni, R., and Gupta, P. (2020). Optimizing Resource Allocation in Flexible Flow Shops using Simio Simulation. International Journal of Production Research, 58(17), 5432-5444.

[5] Tiwari, A., Tang, J., & Xu, Y. (2018). Batching optimization in flexible flow shops: A simulation study. Journal of Manufacturing Systems, 49, 87-98.

[6] Kumar, A., Singh, N., & Kapoor, S. (2017). Discrete-event simulation in stochastic production systems. Journal of Manufacturing Technology Management, 28 (5), 620–641.

[7] Zhang, Z., Zhao, Z., Qin, S., and Liu, S. (2024). Multi-product multi-stage multi-period resource allocation for minimizing batch-processing steel production cost. IEEE Transactions on Automation Science and Engineering, 21(1), 34-47.