International Journal of Mathematical, Engineering and Management Sciences
Vol. 10, No. 6, 1721-1742, 2025
https://doi.org/10.33889/IJMEMS.2025.10.6.082

Ram Arti Publishers

Optimizing Multi-Technician Work Order Scheduling: A Dispatching Rule Algorithm Approach to Reduce Downtime

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(Received on April 16, 2025; Revised on June 17, 2025 & June 20, 2025; Accepted on June 29, 2025)

Abstract
This study investigated the effectiveness of various dispatching rule algorithms in optimizing work-order scheduling involving paired technicians, with a focus on minimizing downtime in industrial maintenance operations. While efficient scheduling is essential for operational productivity, existing approaches often emphasize complex technician utilization analyses that can delay decision-making and exacerbate downtime. Through simulation-based evaluation of seven dispatching rules First Come First Serve (FCFS), Last Come First Serve (LCFS), Round Robin, Longest Processing Time (LPT), Shortest Processing Time (SPT), Weighted Longest Processing Time (WLPT), and Weighted Shortest Processing Time (WSPT), this study measures key performance indicators such as waiting time and repair time. The results reveal that FCFS consistently outperforms other algorithms in reducing downtime, highlighting that technician speed and scheduling responsiveness are more impactful than deep specialization in technician roles. By demonstrating the practical advantages of simpler, rule-based scheduling, this study contributes to the body of knowledge on maintenance optimization and offers actionable insights for industries seeking to streamline technician allocation. Future research should explore AI-based scheduling and dynamic team configurations to further enhance efficiency without introducing unnecessary complexity.

Keywords- Dispatching rule algorithms, Downtime optimization, Paired technician, Scheduling simulations.

1. Introduction

The importance of reducing downtime in modern industries cannot be overstated, as high downtime can lead to significant financial losses and decreased productivity. Understanding how to minimize downtime is a primary objective in industrial operation management. Decades of research have focused on optimizing work order scheduling to minimize downtime. The theory that effective scheduling can enhance the operational efficiency is central to several studies in this field. Poor scheduling is widely assumed to be a major cause of high downtime. There is a longstanding interest in the development of more efficient and adaptive scheduling algorithms. There is a general consensus that high downtime is a serious issue that needs to be addressed to improve industrial productivity. For instance, dispatching rules such as most remaining time first (MRT) are still frequently used as benchmarks in evaluating new scheduling methods, as shown in previous studies (Luo, 2020; Wu et al., 2023). The application of six simple dispatching rules combined with a deep Q-network has also been explored in recent research (Luo et al., 2021), whereas decentralized dispatching rule mechanisms using multi-agent systems have been implemented in other studies (Teck et al., 2023). Importantly, although many studies have focused on multi-agent scenarios, few have specifically emphasized the utilization of multiple technicians. Solutions for job shop scheduling using two agents to determine the optimal objectives in selecting appropriate dispatching rules have been proposed (Luo et al., 2021). Additionally, job prioritization based on multiple criteria later simplified into a single criterion for work order scheduling has been examined (Thenarasu et al., 2024). Based on several studies, traditional dispatching rule methods remain appealing for sequencing work orders involving multiple technicians, whether in terms of scenario design (Quadras et al., 2024) or resource allocation (Voskresenskii et al., 2023a). However, despite the extensive exploration of dispatching rules and agent-based scheduling, limited attention has been given to the specific context of technician pair scheduling in maintenance operations. This represents a gap in the literature, particularly in understanding how traditional dispatching rules perform when applied to real-world scenarios involving technician teams. This study aims to evaluate the effectiveness of various dispatching rule algorithms in optimizing multi-technician work-order scheduling, with a focus on reducing downtime. By addressing this gap, this study contributes to the body of knowledge by providing a comparative analysis of dispatching rules in technician-pair contexts, offering practical insights into maintenance scheduling strategies that balance simplicity and responsiveness. By understanding the strengths and limitations of traditional dispatching rule algorithms, this study aims to provide valuable insights for developing more efficient and adaptive scheduling strategies for multi technician work-order sequencing.

Scheduling algorithms have long been implemented in the industrial sector, primarily to enhance production efficiency tailored to specific situations. In conventional job shop scenarios, the use of simple dispatching rule algorithms remains quite popular, although recent research suggests that newer rules may offer better performance effectiveness (Holthaus & Rajendran, 2000). Some studies have proposed that minimizing the average flow time can reduce the average delay time (Mohanasundaram et al., 2003), while others argue that no single rule is universally optimal for all situations (Zhang & Wang, 2018). In more complex environments, constraint programming has been shown to outperform traditional dispatching rules (Shady et al., 2021; Zhao et al., 2021). Conversely, traditional dispatching rules continue to demonstrate advantages in terms of simplicity and implementation speed, particularly in real-time data applications (Luo et al., 2021). Despite these findings, it remains unclear whether traditional dispatching rules can consistently provide optimal solutions in dynamic and complex environments (Pinciroli et al., 2023; Voskresenskii et al., 2023b). Their effectiveness in multi-technician job assignments aimed at reducing downtime is still an open question. Based on the existing literature, further observation is needed to determine whether traditional dispatching rules can produce optimal work order sequences in such contexts. Evidence supporting the importance of minimizing completion and wait times in reducing downtime was first highlighted in earlier studies (Holthaus & Rajendran, 2000). Three research directions are relevant to this issue. First, some approaches apply dispatching rule algorithms for scheduling optimization, including methods such as the shortest processing time or earliest due date (Mohanasundaram et al., 2003; Zeiträg et al., 2022). Second, other studies focus on optimizing dispatching rule scheduling by considering multi-objective efficiency (Oukil et al., 2022). Third, more advanced algorithms, such as deep reinforcement learning and genetic algorithms, have been explored for complex scheduling problems (Lei et al., 2022; Shi et al., 2023). Overall, it remains uncertain whether traditional dispatching rules can outperform these advanced algorithms under simpler and less complex conditions. Recent studies have shown that although newer scheduling policies such as *Nudge* offer improved performance in job distribution, traditional dispatching rules like First-Come First-Served (FCFS) remain widely used due to their simplicity and robustness, and are still employed as benchmarks in performance evaluations (Grosof et al., 2021). In container terminal operations, for example, FCFS continues to be compared with more advanced methods such as Nearest-Truck-First-Server (NTFS), highlighting its ongoing relevance in various resource allocation scenarios (Riaventin et al., 2024). Therefore, future research could focus on comparing the performance of traditional dispatching rules with that of more advanced approaches.

To reduce machine maintenance downtime based on work-order data involving multiple technicians, traditional dispatching rule techniques offer simple and straightforward solutions, particularly when the data are not overly complex or dynamic. Although traditional dispatching rules remain relevant, they have limitations in addressing the complexities of modern industrial environments (Luo, 2020). More advanced methods have been proposed to learn optimal scheduling rules, yet dispatching rules continue to stand out for their simplicity in implementation and computational efficiency (Wu et al., 2023). For example, neural networks have been used to enhance cost efficiency by learning priority rules for dispatching (Lei et al., 2022; Shi et al., 2023; Zhang et al., 2023). In simulations involving less complex data, simple dispatching rules such as First-Come First-Serve (FCFS), Earliest Due Date (EDD), and Shortest Processing Time (SPT) have proven easy to implement and fast to execute, although they do not always guarantee optimal solutions (Klusáček et al., 2018; Shady et al., 2021; Zhang & Wang, 2018). Although hybrid dispatching rules may offer better performance in terms of optimization, traditional rules remain an attractive choice for simpler conditions where data complexity is low. The primary objective of this research is to evaluate the effectiveness of traditional dispatching rules in optimizing multi-technician work-order scheduling, with a focus on reducing downtime. It is hypothesized that traditional dispatching rules can yield satisfactory results under conditions that are neither overly complex nor dynamic. To investigate this, work order data from the manufacturing industry were collected, and various traditional dispatching rules were applied in the simulation. The results were then compared in terms of downtime reduction. This study includes a comparative analysis of several traditional dispatching rules First-Come First-Serve (FCFS), Last-Come First-Serve (LCFS), Round Robin, Shortest Processing Time (SPT), Longest Processing Time (LPT), Weighted Shortest Processing Time (WSPT), and Weighted Longest Processing Time (WLPT) within the context of multi-technician work order scheduling. The use of dispatching rules in this study aims to observe optimal technician allocation scenarios for minimizing downtime before applying more advanced methods such as metaheuristics. This step is crucial because complex algorithms often face implementation challenges due to data complexity in real-world settings (Faizanbasha & Rizwan, 2025). Dispatching rules, such as FCFS, have been widely proven to be simple, fast, and effective across various scheduling problems, making them suitable for initial scenario testing (Zeiträg & Figueira, 2023).

The remainder of this paper is organized as follows. Section 2 discusses the research methodology, including the research design, data subjects, implementation of dispatching rule algorithms, scheduling procedures, performance measurements, validation, and verification. Section 3 presents the research results, including preprocessing and analysis of the research findings. Section 4 discusses the implications and limitations of this study. The article concludes with a summary, contributions to knowledge, implications for managerial practices, limitations, and opportunities for future research.

2. Research Methods

2.1 Research Design

This study employed a simulation-based approach to evaluate the performance effectiveness of various traditional dispatching rule algorithms for optimizing the scheduling of work orders involving multiple technicians. The goal of this approach is to balance the performance quality and algorithm reliability by incorporating scenarios that reflect resource availability and stochastic factors within the maintenance process (Souza et al., 2022). Simulations were used to test a range of possible scenarios in a controlled and measurable environment, allowing for systematic evaluation without disrupting actual operations (Torres et al., 2024). These simulations were grounded in historical work-order data to ensure realistic modeling of the complexity and dynamics of the maintenance process (Luo et al., 2021). The simulation design steps are as follows:

- The system was modeled to simulate the scheduling of multi-technician work orders using discrete-event simulation software. The model includes key components, such as work orders (μ), technicians (T), machines, team allocations, and dispatching rules based on waiting time (w) and completion time (C). It is assumed that n work orders and m technicians available. Each work order μ_i represents a maintenance task on a specific machine and requires a technician team to perform an operation $\text{ɣ}_{i,j}$, where i^{th} denotes the work order index and j^{th} the sequence of execution. The time required to complete repairing of each operation is denoted by t_{ij}, which includes both waiting time and repair time. Each operation is assigned to a technician pair $\varsigma\{T_{m-1}, T_m\}$, where in this study, the technician team size is fixed at two.

- Historical work-order data were collected to populate the simulation parameters. The dataset includes work order IDs, machine types, job priorities, arrival times, waiting times, completion times, and technician assignments. The set of work orders is represented as Equation (1).

$$\mu = \{\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, , \ldots, \mu_n\} \tag{1}$$

Each work order μ_i requires a processing time t_{ij} and a technician team selected from Equation (2)

$$T = \{T_1, T_2, T_3, T_4, T_5, \ldots., T_m\} \tag{2}$$

The technician allocation for each operation $\text{ɣ}_{i,j}$ is determined based on the availability and suitability of technician pairs ς, with the constraint that each technician can only handle one work order at a time.

- Implementation of dispatching rule algorithms: the dispatching rule algorithms used included First-Come First-Serve (FCFS), Round Robin, Shortest Job First, Longest Processing Time (LPT), Weighted Longest Processing Time (WLPT), and Weighted Shortest Processing Time (WSPT). Each algorithm determines the order in which work orders μ_i are assigned to operations $\text{ɣ}_{i,j}$, executed by technician pairs ς. The scheduling is based on minimizing the total completion time in Equation (3)

$$C_{t,max} = \min\{\max \textstyle\sum_i^n \sum_j^h \left(w_{ij} + t_{ij}\right) \mathit{from}\ \text{ɣ}_{i,j}\varsigma\{T_{m-1}, T_m\}\} \tag{3}$$

where, w_{ij} is the waiting time for operation $\text{ɣ}_{i,j}$, and h is the number of operations per work order.

- Simulation experiments were conducted under various scheduling scenarios, including variations in the number of work orders, technician availability, technician speed, and operational constraints. Two primary technician pairing scenarios were tested in Equation (4) and (5):

$\varsigma \in V_{min}$: technician pairs with the highest speed (4)

$\varsigma \in E_{max}$: technician pairs with the highest expertise (5)

Each operation $\text{ɣ}_{i,j}$ waits for an available technician pair before execution. The constraint is formalized as Equation (6):

$$\varsigma\,(V_{min} \,||\, E_{max}) \in \mu_i \neq \text{ɣ}_{i,j} \tag{6}$$

This ensures that technician allocation is exclusive and sequential.

• The simulation results were analyzed to compare the performance of each dispatching rule. The key performance indicators included in Equation (7) and (8):

Total waiting time $w_{t,min} \in \text{Y}_{dispatch}$ (7)

Total processing time $t_{t,min} \in \text{Y}_{dispatch}$ (8)

The comparison focused on identifying which algorithm produced the most optimal scheduling outcomes under different technician pairing scenarios. These insights were used to determine the relative effectiveness of each rule in handling multi-technician work orders, particularly in terms of reducing delays and improving task completion efficiency.

• Model validation was performed by comparing the simulation outputs with historical data and findings from previous studies. This step ensures that the simulation accurately reflects real-world maintenance operations and provides reliable insights for decision-making.

By utilizing the simulation approach, this study aims to provide in-depth insights into the performance effectiveness of traditional dispatching rule algorithms under various scenarios and offer recommendations for developing more efficient and adaptive scheduling strategies.

2.2 Subject and Data

This study focuses on simulating the scheduling of work orders that require technician teams working in pairs, specifically within the context of machine maintenance operations. The data used in this study were obtained from a Computerized Maintenance Management System (CMMS), which records detailed information about maintenance activities. The primary objective is to optimize dispatching rules to enhance scheduling efficiency and reduce the total time required to complete maintenance tasks, as highlighted in previous studies that emphasized the importance of efficient technician coordination and task allocation (Smith & Srinivas, 2019; Wang & Wu, 2023).

The subjects of this study were work orders that must be executed by two-person technician teams. These teams are assigned based on the nature of the task and the required expertise, ensuring that maintenance is performed effectively and efficiently. The dataset includes several critical attributes: work order identifiers, machine types, arrival timestamps, job priority levels, waiting times, and completion times. Each work-order ID serves as a unique reference for tracking and analysis. Machine information is used to determine technician suitability based on skill specialization. Arrival time data indicate when a work-order enters the system, while job priority reflects the urgency of the task. The waiting time represents the duration for which a work order remains in the queue before being assigned, which is essential for evaluating the responsiveness of the scheduling process. Completion time, on the other hand, captures the full duration from the moment a work order is received until it is finalized, offering a comprehensive measure of scheduling performance.

The structure of this data enables the simulation to realistically model the technician allocation and task execution. By incorporating these variables, the study aims to assess how different dispatching strategies influence operational outcomes, particularly in minimizing delays and maximizing technician productivity in an industrial maintenance setting.

2.3 Implementation of Dispatching Rule Algorithms

This study applied several dispatching rule algorithms within a simulation model to evaluate their effectiveness in scheduling work orders involving multiple technicians (Nasiri et al., 2017). Dispatching rules are widely used in job shop scheduling due to their simplicity and adaptability to real-time data environments (El Khoukhi et al., 2017). The simulation begins by placing incoming work orders each associated with specific equipment and priority levels into a queue. These work orders are then processed based on the selected dispatching rule. When a work order reaches the execution stage, it is assigned to a team of two technicians, in accordance with the study's focus on paired technician scheduling. The simulation model incorporates key elements, such as arrival time, job priority, waiting time, and repair duration, to reflect realistic maintenance operations.

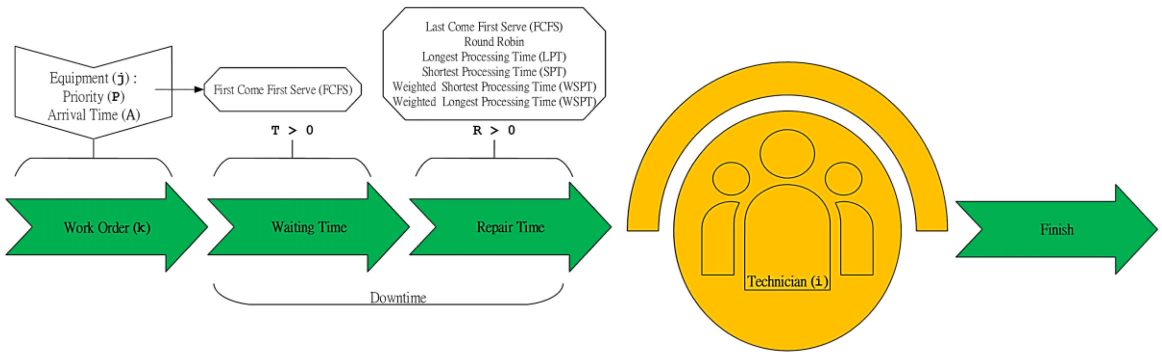

Figure 1. Scheduling process.

The dispatching algorithms in **Figure 1** implemented in this study include several widely used scheduling strategies. First-Come First-Serve (FCFS) prioritizes work orders based on their arrival time, ensuring that tasks are handled in the order they are received. Round robin distributes tasks evenly among technician teams in a rotating sequence, promoting balanced workload distribution. The Longest Processing Time (LPT) gives precedence to tasks with the longest estimated repair duration, whereas the Shortest Processing Time (SPT) gives precedence to tasks with the shortest expected completion time. The Weighted Shortest Processing Time (WSPT) combines job priority and repair time to calculate a weighted score, allowing for more nuanced task sequencing based on both urgency and efficiency. Weighted Longest Processing Time (WLPT), on the other hand, prioritizes tasks by assigning weights based on job priority and then selecting those with the longest weighted processing time, aiming to optimize resource utilization for high-impact tasks.

Each algorithm was coded as a scheduling function in the simulation environment. The simulation was designed using discrete-event logic, where each work order is treated as an event that progresses through the stages of queuing, technician assignment, and task completion. Technician availability was dynamically managed to ensure that no technician was assigned to more than one task at a time. To evaluate the performance of each algorithm, multiple simulation scenarios were conducted, varying in terms of technician availability, task complexity, and job arrival patterns. The simulation results were analyzed based on key performance indicators, including the total completion time, average waiting time, and downtime. These metrics were used to assess the effectiveness of each algorithm in optimizing the scheduling process under different operational conditions.

The outcomes of each scenario were visualized and compared to identify the most efficient dispatching strategy. This approach provides insights into the practical application of dispatching rules in maintenance environments and supports the development of more adaptive and efficient scheduling systems.

2.4 Scheduling Procedure

The experiments in **Figure 2** were conducted using simulations with various parameter variations to evaluate the performance of work-order scheduling involving multiple technicians. The parameters used included the number of work orders, technicians, job priorities, arrival times, waiting times, arrival times, and waiting times. The objective of these experiments was to identify the optimal scenario for scheduling work orders using various dispatching rule algorithms.

Each simulation scenario was conducted by changing parameters such as the arrival time of work orders and job priorities. The adjustment of these parameters aims to determine the best pattern for optimizing scheduling. The dispatching rule algorithms tested included the First-Come First-Server (FCFS), Round Robin, Longest Processing Time (LPT), Shortest Processing Time (SPT), and Weighted Shortest Processing Time (WSPT). Each algorithm was tested for each scenario to evaluate its performance.

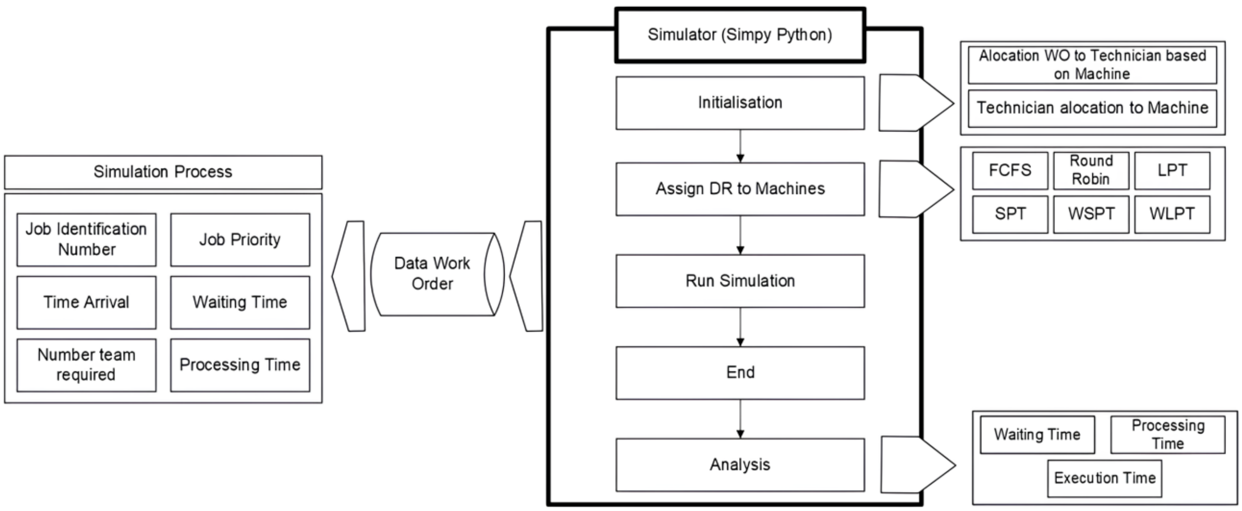

Figure 2. Simulation experiment flow with python.

The waiting time can be minimized by minimizing the total waiting time (Equation (9)). Each work order must be handled by two or more technicians, depending on the equipment requirements (Equation (10)). The starting time of a work order must be greater than or equal to its arrival time (Equation (11)). The completion time of the work order is the start time plus the processing time (Equation (12)). The waiting time is the difference between the start time and arrival time (Equation (13)). There should be no overlap in the work orders of the same technician (Equation (14)).

$$Minimize = \sum_{i=1}^{n} w_i \tag{9}$$

$$\sum_{j=1}^{m} x_{ij} = 2 \; or > 2 \; (for \; each \; i) \tag{10}$$

$$S_i \geq a_i \; (for \; each \; i) \tag{11}$$

$$C_i = S_i + p_i \; (for \; each \; i) \tag{12}$$

$$w_i = S_i - a_i \; (for \; each \; i) \tag{13}$$

$$if \; x_{ij} = 1 \; and \; x_{kj} = 1 \; (i \neq k), then \; C_i \leq S_k \; or \; C_k \leq S_i \tag{14}$$

The following are the general mathematical notations for the scheduling process based on the above scenario. The notation *n* is used for the number of work orders and *m* is used for the number of technicians. The index for work orders is denoted by i (i=1,2,…,n), and the index for technicians is denoted by j (j=1,2,…,m). The start time of the i-th work order is denoted as S_i, and the completion time of the i-th work order is denoted as C_i. The repair time of the ith work order is represented by p_i, while the arrival time of the i-th work order is denoted by a_i. The waiting time of the ith work order is denoted as w_i. The binary variable x_{ij} equals 1 if the ith work order is performed by the jth technician, and 0 otherwise. The availability of the jth technician (e.g., working hours) is denoted as T_j.

Based on general scenarios and mathematical notations, the use of simple dispatching rules can be illustrated using the following concepts, encompassing various implementable scenarios.

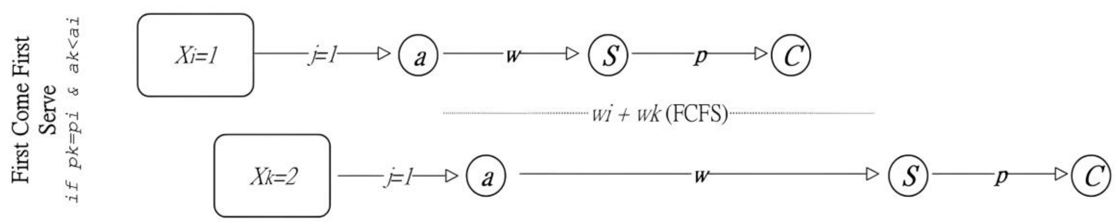

Figure 3. First come first serve (FCFS).

In **Figure 3**, the FCFS concept, the scenario is performed by allocating work orders based on arrival times. The repair times between p1 and p2 may or may not differ, and work orders are assigned to the same paired technicians based on their arrival times (Teymourifar et al., 2020).

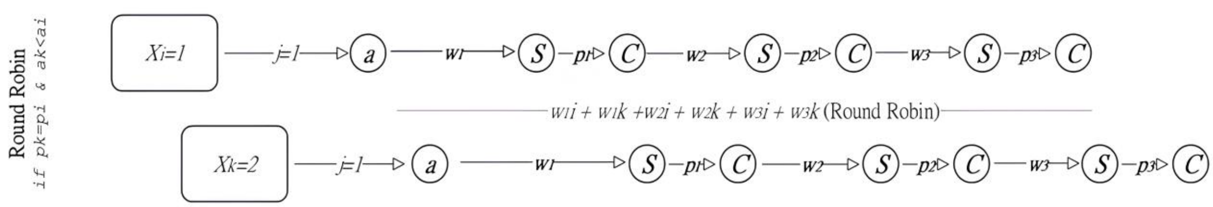

Figure 4. Round robin.

In **Figure 4**, the round-robin scenario is similar to FCFS, but the repair times are limited to a predetermined time p. The first and second tasks were performed alternately with fair distribution until the repair process was completed (Alexopoulos et al., 2024).

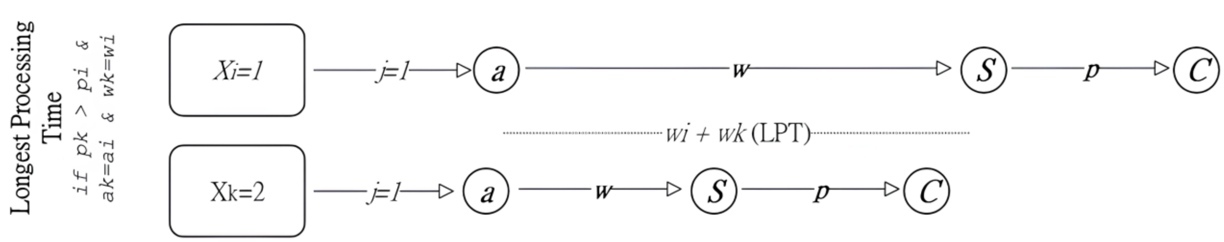

Figure 5. Longest processing time (LPT).

In **Figure 5** and **6**, the LPT and SPT scenarios, dispatching rules were implemented by comparing repair times with the same arrival times. In the LPT, tasks with the longest repair times are prioritized, whereas in the SPT, tasks with the shortest repair times are prioritized. Repair times are sequentially managed until the technicians complete their tasks according to the repair time priorities (Ferreira et al., 2020).

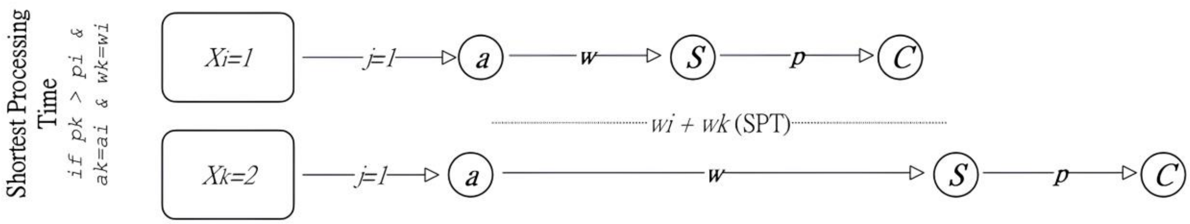

Figure 6. Shortest processing time (SPT).

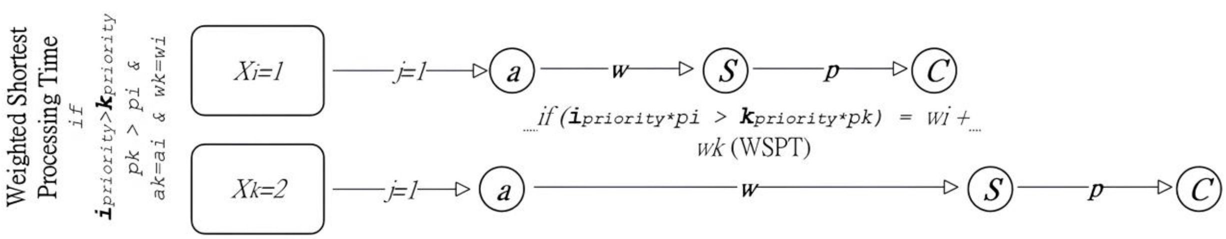

Figure 7. Weighted shortest processing time (WSPT).

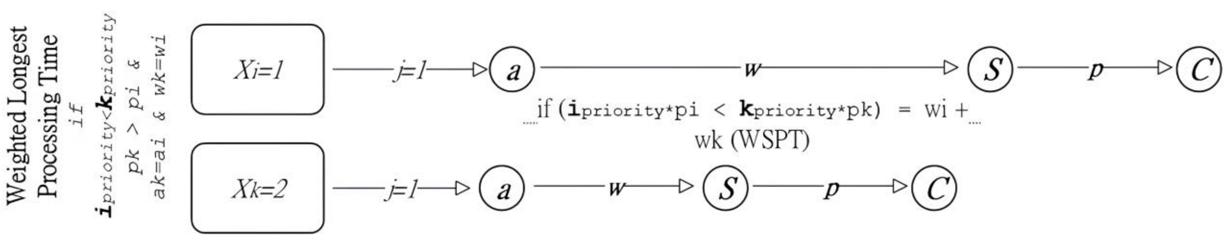

Figure 8. Weighted longest processing time (WLPT).

In the **Figure 7** and **8**, although WSPT and WLPT appear similar to SPT and LPT, at first glance, the difference lies in the implementation of weights based on the priority levels of the tasks. These weights are determined based on the repair times and job priorities. These scenarios were based on the allocation of paired technicians, which were tested using multiple teams.

Simulations were conducted for each scenario using the Python simulation software. The simulation results include performance metrics, such as completion time, waiting time, and downtime. Each algorithm was evaluated based on these metrics to determine its effectiveness.

The results of the simulation experiments were analyzed to compare the performance of the various dispatching rule algorithms. With the aid of statistical analyses, such as histograms and statistical measurements, significant differences between algorithms can be evaluated to determine the most effective algorithm for optimizing multi-technician work-order scheduling. Subsequently, the simulation model was validated by comparing the simulation results with historical data. This validation is crucial to ensure that the simulation model is accurate and reliable for developing more efficient and adaptive scheduling strategies.

2.5 Scheduling Performance Measurement

Dispatching rules can be used to evaluate various scenario methods in automated vehicle storage (Lupi et al., 2024), which can be utilized to measure the impact of implementing different strategies aimed at reducing downtime and increasing technician productivity (Wu et al., 2023). Based on **Figure 9**, three measurement scenarios were used to evaluate the effectiveness of the dispatching rule algorithms. SC1 (Scenario 1) does not consider technician speed and relies on historical data; SC2 (Scenario 2) considers technician speed based on the average speed of two technicians using simulation data; and SC3 (Scenario 3) considers the fastest technician speed for completion time using simulation data.

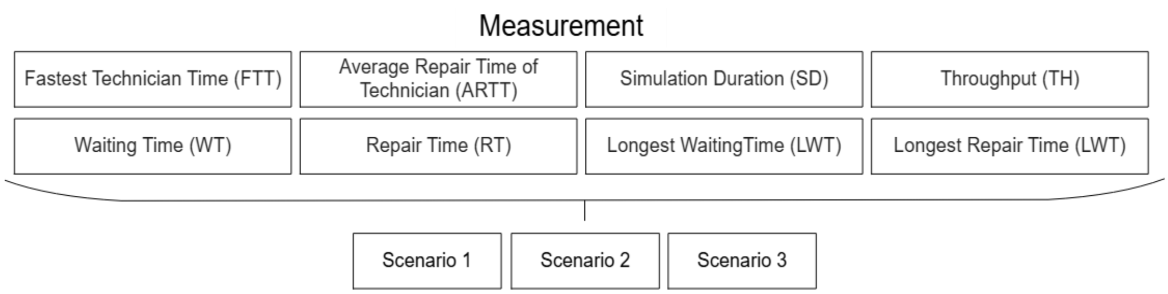

Figure 9. Performance measurement.

The performance metrics in **Figure 9**, used to evaluate the effectiveness of the dispatching rule algorithms, include the Fastest Technician Time (FTT), which measures the fastest time taken by a technician to complete tasks, indicating efficiency in handling urgent tasks. Average repair time of technician (ARTT), which provides an overview of technicians' speed and effectiveness in completing repairs. The Simulation Duration (SD) measures the overall duration of scheduling and task completion processes, with shorter durations indicating quicker responsiveness. Throughput (TH) measures the number of jobs or tasks completed within a certain period, reflecting the efficiency of the scheduling system. Waiting Time (WT), which measures the time spent by work requests in the queue before processing, with lower times indicating faster handling and increased customer satisfaction. Repair Time (RT), which measures the time taken to complete repairs from start to finish, indicates technicians' efficiency. the Longest Waiting Time (LWT), which measures the longest wait time in the queue, assesses the scheduling system's efficiency in handling urgent requests. and Longest Repair Time (LRT), which measures the longest repair time required by technicians, indicating their effectiveness in handling complex tasks.

Using these performance metrics, this study evaluated the effectiveness of various dispatching rule algorithms in optimizing downtime and increasing technician productivity (Ismail et al., 2024). This evaluation was conducted in a prepared simulation environment (Zhao et al., 2021). The performance analysis results provide valuable insights into the most effective dispatching rule algorithms for scheduling work requests involving paired technicians.

2.6 Validation and Verification

The validation and verification of this study were conducted through trials using two randomly selected data samples from the work-order data. These two samples were obtained by simulating predetermined scenarios to evaluate the results from samples 1 and 2. By observing these two samples in scheduling simulations, we expect to provide an accurate analysis of the overall scheduling results, particularly in efforts to reduce downtime.

In this study, validation was performed by ensuring that the data used in the simulation reflected the actual conditions of work requests and technician availability (Wang et al., 2024; Xu et al., 2024). Verification was performed by comparing the simulation results from scenarios 2 and 3 with the historical data used in scenario 1 or with relevant benchmarks. The goal was to ensure the consistency and reliability of the results.

To conduct the simulation, we used SimPy, a Python library that allows discrete process simulations. This included several performance metrics: Waiting Time (WT), Repair Time (RT), Longest Waiting Time (LWT), Longest Repair Time (LR), Fastest Technician Time (FTT), Average Repair Time of Technician (ARTT), Simulation Duration (SD), and Throughput (TH). The simulation results were then analyzed and presented in a graphical form to facilitate interpretation.

In sample 1 in **Table 1**, the work requests involved four pieces of equipment, each of which had at least two technicians.

Table 1. Sample 1.

EQP	TCH 1	TCH 2	TCH 3
GTOM1	ALF	IMI	IAN
VCBU1	ALF	UDA	IAN
WPM15	UDA	SAN	SAN
VCBU4	IMI	UDA	

EQP = Equipment, TCH = Technician.

In sample 2 in **Table 2**, the work request simulation involved 19 pieces of equipment, with 17 technicians allocated in pairs for each work request.

Table 2. Sample 2.

EQP	TCH 1	TCH 2	TCH 3
CAMN1	ROB	GUH	IMA
CAMN2	ROB	SAN	UDA
CDCAS1	WID	IRA	
DRCAS1	WID	IRA	
CACAS8	WID	IRA	ECA
IRMNT3	ROB	JAH	ENU
SSTECH2	WID	IRA	
IRMNT4	ROB	SAN	UDA
CBCAS6	HIM	GON	
CBCAS7	ECA	DIN	GIM
IRMNT5	ECA	DIN	
CECAS9	WID	IRA	
SSTECH3	ECA	DIN	
CCAST4	ECA	DIN	
SBSCTE1	ECA	DIN	
IRMNT1	GUH	IRS	
CDCAS8	ECA	DIN	
CDCAS6	ECA	DIN	
CDCAS3	ECA	DIN	

EQP = Equipment, TCH = Technician.

Using these two samples, the scheduling simulation results can be validated and verified to ensure that the dispatching rule algorithm and scenarios are effective in reducing downtime and increasing technician productivity. The analysis of these two samples is expected to provide comprehensive and accurate insights into the effectiveness of scheduling work requests involving paired technicians.

3. Results

3.1 Data Preprocessing

The first step in this research involved selecting two samples from different work-order datasets for scheduling simulations. The sample data included work requests that occurred over a full day. Information was extracted from the work order dataset, including the columns for equipment, priority, arrival time, waiting time, and repair time. General information obtained from the work request data includes the following: arrival time, based on the date and time when a work request is created; Waiting Time, measured from the moment the work request is confirmed by the maintenance team until a technician is allocated; and repair time, measured from the moment the work request is received by the technician until the job is completed.

After obtaining samples from the work request data, the next step was data preprocessing to ensure the quality of the data used in the simulation. The preprocessing steps included invalid data removal, which involved eliminating the arrival time, waiting time, and repair time values that were null or negative to ensure an accurate analysis. Technician data extraction was performed based on historical technician requirements from the work request data, and all sample data from work requests that did not involve paired technicians were removed to ensure that only work order data with paired technician allocations were used in the simulation. Finally, data transformation was conducted by converting waiting time and repair time data into seconds or minutes to ensure a uniform format and ease of analysis, which is crucial for simplifying calculations and interpreting simulation results

By performing these preprocessing steps, the data used in the scheduling simulation became cleaner and more ready for analysis. **Table 3** shows an example of sample data from work orders that have undergone preprocessing.

Table 3. Example of sample work orders data.

WO	EQP	PRT	TMA	WT (Mnt)	RT (Mnt)	TCH 1	TCH 2
WO035571	GTOM1	C	00:00:00	4	13	ALF	IMI
WO035595	VCBU1	A	00:01:00	6	46	ALF	IMI
WO035610	WPM15	A	00:04:00	2	20	ALF	IMI
WO035687	VCBU4	B	00:03:00	7	35	ALF	IMI
WO035688	VCBU4	A	00:04:00	5	34	ALF	IMI
WO035689	VCBU4	C	00:06:00	2	204	ALF	IMI
WO035735	WPM15	A	00:05:00	2	116	ALF	IMI
WO035829	GTOM1	B	00:07:00	4	25	ALF	IMI
WO035834	VCBU1	B	00:08:00	7	23	ALF	IMI

WO = Work Order, EQP = Equipment, PRT = Priority, TMA = Time Arrival, WT = Waiting Time, Mnt = Minute, TCH = Technician.

3.2 Analysis of Research Results

A simulation was conducted to analyze the effectiveness of dispatching rule algorithms and identify the most productive and efficient scenarios for handling downtime in work orders involving paired technicians. The primary objective of this analysis is to provide insights into the performance of dispatching rule algorithms in the context of paired technician scheduling and downtime reduction.

This analysis includes several key performance metrics, such as Waiting Time (WT), repair time (RT), Longest Waiting Time (LWT), Longest Repair Time (LRT), Fastest Technician Time (FTT), Average Repair Time Of Technician (ARTT), Simulation Duration (SD), and Throughput (TH). These metrics are measured in seconds to provide a clear understanding of the scheduling efficiency.

Tables 4 and **5** present the results obtained from the simulation process using the dispatching rule algorithms. The data displayed in these tables reflect the performance of the dispatching rule algorithms across the three scheduling scenarios, highlighting their effectiveness in reducing downtime and enhancing technician productivity.

Table 4. Sample simulation results 1.

DR	**WT**			**RT**			**LWT**			**LRT**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
FCFS	121380	119050	111400	30960	37100	34800	59580	50040	46740	16380	11100	10800
LCFS	153120	107280	100680	30960	37100	34800	47880	41960	39160	16380	11100	10800
R. Robin	826440	2196460	1848800	30960	37100	34800	525420	779330	636280	16380	11100	10800
LPT	153840	106730	100280	30960	37100	34800	49980	44990	42240	16380	11100	10800
SPT	155760	145380	135480	30960	37100	34800	60060	61460	57160	16380	11100	10800
WLPT	153840	106730	100280	30960	37100	34800	49980	44990	42240	16380	11100	10800
WSPT	155760	145380	135480	30960	37100	34800	60060	61460	57160	16380	11100	10800
DR	**FTT**			**ARTT**			**SD**			**TH**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
FCFS	1605	3250	3000	15480	18550	17400	30540	34090	32040	0.0003	0.0003	0.0003
LCFS	1605	3250	3000	15480	18550	17400	28800	30720	28920	0.0003	0.0003	0.0003
R. Robin	493.84	286.7	290.32	15480	18550	17400	30720	34210	32160	0.0018	0.0038	0.0037
LPT	1605	3250	3000	15480	18550	17400	28800	30720	28920	0.0003	0.0003	0.0003
SPT	1605	3250	3000	15480	18550	17400	31080	37220	34920	0.0003	0.0002	0.0003
WLPT	1605	3250	3000	15480	18550	17400	28800	30720	28920	0.0003	0.0003	0.0003
WSPT	1605	3250	3000	15480	18550	17400	31080	37220	34920	0.0003	0.0002	0.0003

FCFS = First Come First Serve, LCFS = Last Come First Serve, Round Robin, LPT = Longest Processing Time, SPT = Shortest Processing Time, WLPT = Weighted Longest Processing Time, WSPT = Weighted Shortest Processing Time.

Table 5. Sample simulation results 2.

DR	**WT**			**RT**			**LWT**			**LRT**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
FCFS	556500	2651816	227444	215880	1438829	118411	141000	1227558	56856	76320	1233962	23880
LCFS	826260	4173669.5	544816	215880	1438829	118411	198120	1255698	141995	76320	1233962	23880
R. Robin	11794800	2655101258	4532672	215880	1438829	118411	215880	2642011726	957600	76320	1233962	23880
LPT	852960	4171589.5	557488	215880	1438829	118411	190860	1255698	141995	76320	1233962	23880
SPT	812760	4179164.5	547098	215880	1438829	118411	191220	1255698	139166	76320	1233962	23880
WLPT	835080	4171137	538661	215880	1438829	118411	183960	1255698	141995	76320	1233962	23880
WSPT	835080	4179617	565925	215880	1438829	118411	183960	1255698	139166	76320	1233962	23880
DR	**FTT**			**ARTT**			**SD**			**TH**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
FCFS	2430	4794.2	3096.2	39250.9	261605	21529.3	63060	60728	62210	0.0004	0.0004	0.0004
LCFS	2430	4794.2	3096.2	39250.9	261605	21529.3	63360	39000	36170	0.0004	0.0006	0.0007
R. Robin	540	289.58	180	39250.9	261605	18217.1	63180	63480	63480	0.0059	0.0758	0.0064
LPT	2430	4794.2	3096.2	39250.9	261605	21529.3	63360	39000	36170	0.0004	0.0006	0.0007
SPT	2430	4794.2	3096.2	39250.9	261605	21529.3	63420	39000	36170	0.0004	0.0006	0.0007
WLPT	2430	4794.2	3096.2	39250.9	261605	21529.3	63420	39000	36170	0.0004	0.0006	0.0007
WSPT	2430	4794.2	3096.2	39250.9	261605	21529.3	63420	39000	36170	0.0004	0.0006	0.0007

FCFS = First Come First Serve, LCFS = Last Come First Serve, Round Robin, LPT = Longest Processing Time, SPT = Shortest Processing Time, WLPT = Weighted Longest Processing Time, WSPT = Weighted Shortest Processing Time.

By analyzing the research results, this study aims to answer the research question (RQ): "How effective are traditional dispatching rule algorithms in reducing downtime in work order data involving paired technicians?" The researchers hypothesized that the use of traditional dispatching rule algorithms and appropriate scenarios can significantly reduce downtime in work orders involving paired technicians.

To test this hypothesis, simulations were conducted using dispatching rule algorithms on two samples of work order data, encompassing key performance metrics such as Waiting Time (WT), Repair Time (RT), Longest Waiting Time (LWT), Longest Repair Time (LRT), Fastest Technician Time (FTT), Average Repair Time of Technician (ARTT), Simulation Duration (SD), and Throughput (TH). The simulation results indicate a significant relationship between the use of dispatching rule algorithms and the scenarios employed to reduce the work order downtime. By observing waiting and repair times, other relevant metrics can be identified, providing insights into the effectiveness of dispatching rule algorithms in reducing downtime and enhancing technician productivity.

4. Discussion

4.1 Implications

This study investigated the effectiveness of traditional dispatching rule algorithms in optimizing downtime related to scheduling work orders involving paired technicians. This study addresses the question of whether the use of dispatching rule algorithms can enhance efficiency and productivity in multi-agent scenarios, particularly those involving multiple technicians. The objective of this study is to evaluate the effectiveness of traditional dispatching rule algorithms in reducing downtime and improving technician productivity. This assertion is supported by the lack of related research focusing on multi-agent scenarios, especially those involving multiple technicians (Teck et al., 2023). Scheduling that involves more than two resources or agents can leverage dispatching rule algorithms to achieve optimal objectives (Luo et al., 2021). These algorithms remain relevant and effective in certain underexplored and challenging cases (Luo, 2020; Wu et al., 2023). In addition, it seeks to identify the best scenarios for achieving optimal results. The findings indicate that the First-Come First-Served (FCFS) algorithm is more efficient than other dispatching rule algorithms such as Last-Come First-Served (LCFS), Round Robin, Longest Processing Time (LPT), Shortest Processing Time (SPT), Weighted Longest Processing Time (WLPT), and Weighted Shortest Processing Time (WSPT). Furthermore, technician allocation scenarios focusing on selecting technicians based on their speed in handling work requests significantly impact downtime optimization.

This research demonstrates the effectiveness of using dispatching rule algorithms to optimize downtime for work-order scheduling. By sequencing work orders according to arrival time and considering technician speed in handling work orders, this study shows that technician productivity in managing downtime can be improved. The scheduling simulation of dispatching rules indicates that these algorithms remain relevant in challenging case studies such as handling work requests with paired technicians. There are three possible explanations for this finding. First, dispatching rule algorithms that sequence work orders based on arrival time can significantly reduce waiting times, because technicians can promptly address earlier requests. Second, considering the technician's scheduling speed can enhance efficiency, as faster technicians can complete more tasks in a shorter time. Third, using dispatching rules in paired technician scenarios can optimize resource allocation, thereby reducing downtime and increasing productivity.

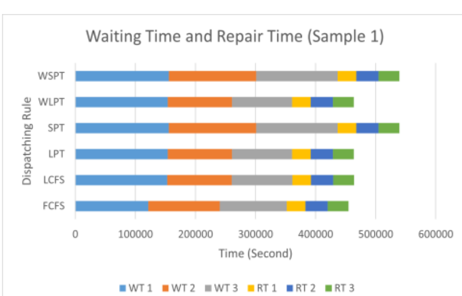

Figure 10. WT and RT for sample 1.

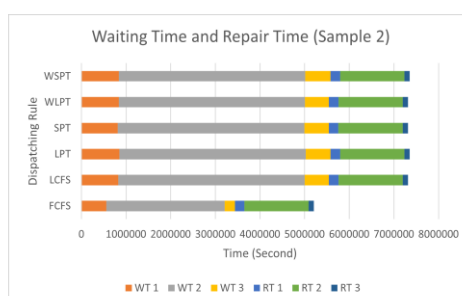

Figure 11. WT dan RT for sample 2.

Sample graphs 1 and 2 in **Figures 10** and **11** illustrate the optimization of downtime in scheduling work requests involving paired technicians. Based on the simulation data obtained, several dispatching rules were tested, including FCFS, LCFS, LPT, SPT, WLPT, and WSPT, except for round robin, which, according to **Tables 4** and **5**, is the least efficient. The simulation results show variations in Waiting Time (WT) and Repair Time (RT) for each scenario. From these results, it can be observed that the dispatching rules for samples 1 and 2 in scenario 1 exhibit better performance than those in scenarios 2 and 3, in terms of waiting and repair times. This is evident from the lower WT and RT values in scenario 1 than in the other scenarios.

Optimization of the downtime in scheduling work requests involving paired technicians can be achieved by selecting the most efficient dispatching rule. Based on the simulation results, the FCFS dispatching rule demonstrates the most optimal results with a lower waiting time and repair time compared to other dispatching rules, although round robin has a lower waiting time, but a higher repair time compared to FCFS. This indicates that scheduling using the FCFS method can significantly reduce downtime, thereby increasing the technician efficiency and productivity.

According to the dispatching rule graphs above, scenario 1 (FCFS) outperformed scenario 2 (LCFS) in terms of scheduling implementation using dispatching rules, in terms of both waiting time and repair time. Therefore, to optimize downtime in scheduling work requests involving paired technicians, the FCFS method can be considered the most effective choice, if the focus is on minimizing downtime in terms of Waiting Time (WT) And Repair Time (RT).

One possible explanation for these research findings is that the First-Come First-Served (FCFS) dispatching rule algorithm shows better performance than other algorithms because it is simple and straightforward, allowing technicians to promptly address work requests without needing to consider additional priorities or complexities. Contrary to statements suggesting that simple dispatching rules lack quality and are difficult to implement in dynamic scenarios (Luo, 2020), the most important aspect of the scheduling process is minimizing waiting time in work-order processing to reduce downtime (Holthaus & Rajendran, 2000).

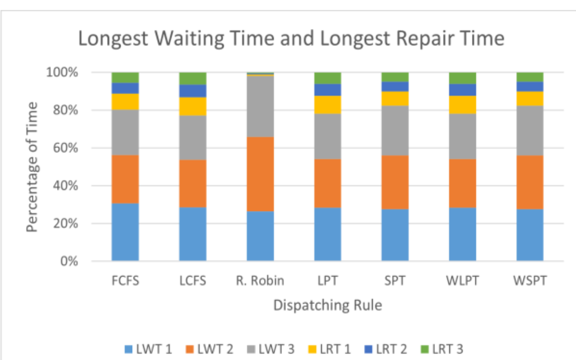

Figure 12. LWT and LRT for sample 1.

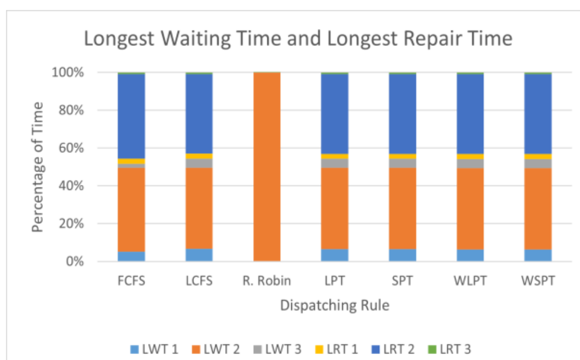

Figure 13. LWT and LRT for sample 2.

Based on the simulation data analysis obtained from **Figures 12** and **13**, which depict the Longest Waiting Time (LWT) And Longest Repair Time (LRT), several dispatching rules were tested, including FCFS, LCFS, Round Robin, LPT, SPT, WLPT, and WSPT. The simulation results showed variations in the LWT and LRT for each scenario. The FCFS dispatching rule demonstrated superior performance compared to other dispatching rules in terms of waiting time and repair time. The average LWT and LRT for FCFS were the lowest among all the dispatching rules tested. This indicates that scheduling using the FCFS method can significantly reduce downtime, thereby enhancing technician efficiency and productivity.

The LCFS dispatching rule also showed relatively good performance but was still outperformed by the FCFS. The round-robin dispatching rule exhibited the poorest performance, with the highest average LWT and LRT. This suggests that the round-robin method is ineffective for scheduling work requests involving paired technicians. Other dispatching rules, such as LPT, SPT, WLPT, and WSPT, showed varying performance but were still inferior to FCFS.

Based on this analysis, it can be concluded that the FCFS method is the most effective for optimizing the downtime for scheduling work requests involving paired technicians. Another possible explanation for these findings is that the round-robin dispatching rule algorithm is less effective in reducing downtime because it does not consider technician speed or the urgency of work requests, potentially leading technicians to suboptimal scheduling. Although the Enhanced Round Robin (ERR) algorithm has demonstrated improved performance over traditional round robin by reducing average waiting time for tasks, this enhancement is primarily observed in CPU scheduling contexts and may not be directly applicable to the scheduling of technician work requests (Sanaj & Prathap, 2020).

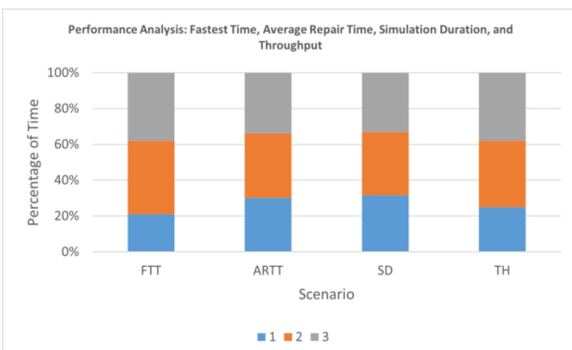

Figure 14. FTT, ARTT, SD TH for sample 1.

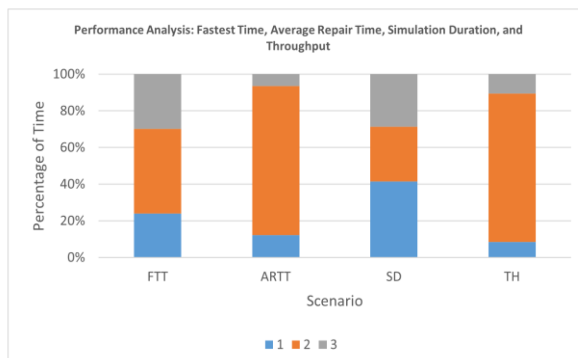

Figure 15. FTT, ARTT, SD TH for sample 2.

Based on the simulation data analysis obtained from **Figures 14** and **15** for the two samples, several technician performance metrics were tested across three different scenarios. The metrics analyzed included the Fastest Technician Time (FTT), Average Repair Time of Technician (ARTT), Simulation Duration (SD), and Throughput (TH). From the simulation data analysis, it is evident that scenarios with lower average FTT and ARTT demonstrate better performance. A lower FTT indicates that technicians can complete their tasks in a shorter time, reflecting high efficiency in handling urgent tasks. A lower ARTT indicates that the average time required for technicians to complete repairs is shorter, indicating that technicians work faster and more effectively.

Additionally, a shorter Simulation Duration (SD) indicates that the overall scheduling and task completion process is faster, thereby reducing waiting time and enhancing responsiveness to work requests. This is crucial in situations where time is a critical factor, such as urgent repairs or dynamic work environments. A Higher Throughput (TH) indicates that more work can be completed within a given time period, implying that the scheduling system can handle a larger volume of work with higher efficiency. The high throughput also suggests that technicians can complete more tasks without compromising the quality of their work.

Based on this analysis, scenarios with the lowest FTT and ARTT values and the highest throughput can be considered optimal. These scenarios not only reduce downtime but also enhance overall technician productivity. By selecting an optimal scenario, companies can ensure that their technicians work with maximum efficiency, thereby improving customer satisfaction and reducing operational costs. While Overall Equipment Effectiveness (OEE) values, including availability, performance efficiency, and rate of quality, are crucial for identifying areas for improvement in manufacturing processes (Alexander et al., 2024), they cannot be used as a benchmark for technician allocation. This is because OEE primarily focuses on equipment performance and does not account for variables such as technician speed, skill level, or task urgency, which are essential for effective scheduling.

According to the information provided, the third scenario demonstrated better productivity and efficiency than the other scenarios. This is because of the lower FTT, ARTT, and SD values, which indicates that technicians can complete their tasks more quickly and efficiently. Although the Throughput (TH) in the third scenario was lower than that in the second scenario, the second scenario showed higher FTT, ARTT, and SD values, indicating that technicians took longer to complete their tasks, and the simulation duration was longer. Therefore, despite the higher throughput in the second scenario, the third scenario remains more productive and efficient overall because of shorter task completion times and more efficient simulation durations.

Thus, the third scenario can be considered the best for optimizing downtime and enhancing technician productivity when scheduling requests involving paired technicians. This scenario ensures that technicians can complete their tasks quickly and efficiently, thereby improving the overall operational efficiency. Therefore, to optimize downtime in scheduling work requests involving paired technicians, the method that yields the lowest FTT and ARTT values and the highest throughput is the most effective choice.

Table 6. Min, max, mean values of waiting time and repair time.

Descriptive analysis indicators	Minutes					
	WT			RT		
	1	2	3	1	2	3
Mean	39317.71	6377686	17890.72	3598	23980	1973.5
Min	9275	44196	3790.7			
Max	196580	44251687	75544.5			

Table 6 lists the average Waiting Time (WT) and Repair Time (RT) for each scenario. It is important to note that scenario 1 represents historical data samples, whereas scenarios 2 and 3 include simulated data incorporating technician speed. Scenario 1 shows that the average WT is quite high, ranging from 9,275 to 196,580 min, indicating that historical scheduling methods may not be efficient in reducing waiting time. The average RT in this scenario was 3,598 min, showing consistency, but still relatively high.

Scenario 2 exhibits an extremely high average WT, ranging from 44,197 to 44,251,688 min, suggesting that the scheduling method in this simulation may not be effective in reducing the waiting time. The average RT in this scenario was 23,980 min, which was significantly higher than that in scenario 1, indicating longer repair times.

Scenario 3 shows a lower average WT compared to scenario 2, ranging from 3,791 to 9,432 min, indicating that the scheduling method in this simulation is more effective in reducing the waiting time compared to scenario 2. The average RT in this scenario is 1,973 min, which is lower than that in both scenarios 1 and 2, indicating faster repair times in this simulation.

It is noteworthy that scenario 1 demonstrates better performance in terms of lower RT compared to Scenario 2, but has a very high WT. Scenario 2 (simulated data) shows poor performance with very high WT and RT values, indicating that the scheduling method in this simulation is ineffective. Scenario 3 (Simulated Data) shows better performance with lower WT and RT compared to scenarios 1 and 2, indicating that the scheduling method in this simulation is more effective. From these results, it can be concluded that scenario 3 is the most effective in reducing waiting and repair times, whereas scenario 2 shows the worst performance. Although scenario 1 had lower repair times, it still had significantly longer waiting times.

These findings provide a new perspective, in that simple dispatching rule algorithms, particularly FCFS, remain superior in addressing scheduling issues for work orders involving multiple technicians. Scenarios related to technician selection are highly effective when technician allocation is based on speed. This indicates that technician selection in work order scheduling is not only determined by knowledge but can also involve technician speed as a parameter. These findings prove that traditional dispatching rules remain relevant for addressing issues in modern industrial environments (Luo, 2020).

This study resolves the conflict between scheduling efficiency and technician speed, showing that technician speed is a crucial factor for effective scheduling. Technician allocation has been of key interest in scheduling processes for several years. These findings further reveal that a significant technician speed reduces downtime. Additionally, it introduces a new approach to handling multi-technician work order scheduling, demonstrating that the first-come first-serve rule still has the capability to reduce downtime better than others by maximizing technician speed in task completion.

4.2 Limitations

Our study has several key limitations that should be considered when interpreting the results. First, the assumptions made in this study, such as scheduling in the simulation that does not account for technician arrival times, may have affected the findings. The arrival times were used only for data sequencing and were not included in the simulation; thus, they did not fully reflect the real-world conditions. Additionally, paired technicians were allocated based on their expertise in specific equipment, which may not fully represent the flexibility required for field assignments.

Second, this study did not include scenarios related to technicians' shift work. All technicians were assumed to always be available for scheduling, which is unrealistic given work hour limitations and the need for rest. Furthermore, each technician was assigned only one work request per simulation to avoid a high workload, which may not reflect the actual workload of technicians.

Third, there were no time constraints on the technician tasks for each request, or limitations on the number of technicians involved. If two job requests arrive simultaneously, they are not processed concurrently but are adjusted based on the availability of equipment and technicians. This can lead to unanticipated delays in the simulation.

Regarding the data used, this study involved two randomly selected data samples to evaluate the effectiveness of the algorithms and the best scheduling scenarios for reducing downtime. However, this research focused solely on the use of dispatching rule algorithms for sequencing work requests involving paired technicians and did not include more advanced algorithms, such as artificial intelligence. Although some advanced algorithms have been implemented to address issues such as dynamic scheduling with real-time job arrivals (Wu et al., 2023; Xu et al., 2024) and adaptive resource allocation using differential evolution (Li et al., 2023), this limits the generalizability of the findings to more complex and dynamic scheduling scenarios.

Although alternative explanations for our results cannot be ruled out, the two patterns in the findings point to the main explanations. First, the results indicate that traditional dispatching rule algorithms, such as FCFS, remain relevant and effective in reducing downtime in paired technician scheduling scenarios. Second, technicians' speed of handling work orders is a crucial factor that can enhance efficiency and productivity.

However, it is important to note that in this study, the performance of FCFS was observed only under specific conditions, namely, technician allocation based on expertise and work speed. The algorithm did not account for other potentially influential factors, such as technician workload distribution or scenarios where waiting time is excluded from the scheduling criteria. Furthermore, the scheduling scenario did not incorporate job priority levels or consider the varying capacities of technicians to handle different workloads. These limitations suggest that while FCFS can be effective in certain contexts, its applicability may be constrained in more complex or dynamic scheduling environments where prioritization and resource balancing are critical.

It is hoped that future research will address these limitations and provide more comprehensive and accurate results in the context of scheduling work requests involving technicians.

5. Summary and Conclusion

This study investigated the effectiveness of dispatching rule algorithms in optimizing downtime for scheduling work orders involving paired technicians. Previous research suggests that traditional dispatching rule algorithms can still be effectively used in complex scheduling scenarios (Wu et al., 2023), and the use of two agents can determine the optimal objectives of the appropriate dispatching rule (Luo et al., 2021). This study offers a new perspective on the importance of technician speed in scheduling work orders involving paired technicians.

The findings indicate that the First-Come First-Served (FCFS) dispatching rule algorithm is superior to other algorithms in reducing downtime and enhancing technician productivity. These insights highlight that technician speed is a key factor in effective scheduling and is applicable to various industrial scenarios. Additionally, the study revealed that allocating technicians based on their speed of handling work orders can be more effective than allocations based solely on technical skills.

The implications of this study are that companies can improve their operational efficiency and technician productivity by implementing dispatching rule algorithms that consider technician speed. This can significantly reduce downtime and enhance the responsiveness to work requests.

Future research could explore the use of more advanced algorithms, such as artificial intelligence, to further improve the efficiency and productivity of technician scheduling. Further studies could investigate more complex and dynamic scheduling scenarios using real-time data and test dispatching rule algorithms under various industrial conditions.

Conflict of Interest

The authors declare no conflict of interest regarding the publication of this paper.

Acknowledgments

I thank my younger brother, Fahrur Rozi, for his valuable input and technical assistance. Finally, I wish to express my gratitude to my family, who provided unwavering support and understanding throughout this research process.

AI Disclosure
During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Alexopoulos, K., Mavrothalassitis, P., Bakopoulos, E., Nikolakis, N., & Mourtzis, D. (2024). Deep reinforcement learning for selection of dispatch rules for scheduling of production systems. *Applied Sciences*, *15*(1), 232. https://doi.org/10.3390/app15010232.

El Khoukhi, F., Boukachour, J., & Alaoui, A.E.H. (2017). The "dual-ants colony": a novel hybrid approach for the flexible job shop scheduling problem with preventive maintenance. *Computers & Industrial Engineering*, *106*, 236-255. https://doi.org/10.1016/j.cie.2016.10.019.

Faizanbasha, A., & Rizwan, U. (2025). Optimizing burn-in and predictive maintenance for enhanced reliability in manufacturing systems: A two-unit series system approach. *Journal of Manufacturing Systems*, *78*, 244-270. https://doi.org/10.1016/j.jmsy.2024.12.002.

Ferreira, C., Figueira, G., Amorim, P. (2020). Optimizing dispatching rules for stochastic job shop scheduling. In: Madureira, A., Abraham, A., Gandhi, N., Varela, M. (eds) *Hybrid Intelligent Systems. HIS 2018. Advances In Intelligent Systems and Computing* (Vol. 923, pp. 321-330). Springer Cham, Switzerland. https://doi.org/10.1007/978-3-030-14347-3_31.

Grosof, I., Yang, K., Scully, Z., & Balter, M.H. (2021). Nudge: stochastically improving upon FCFS. *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, *5*(2), 1-29. https://doi.org/10.1145/3460088.

Holthaus, O., & Rajendran, C. (2000). Efficient jobshop dispatching rules: further developments. *Production Planning & Control*, *11*(2), 171-178. https://doi.org/10.1080/095372800232379.

Ismail, M.H., Chiachío, M., Chiachío, J., Arranz, F., & Saleh, A. (2024). A computer-based simulation methodology of the predetermined maintenance scheme of an irradiation facility. *Computers & Industrial Engineering*, *198*, 110671. https://doi.org/10.1016/j.cie.2024.110671.

Klusáček, D., Matyska, L., & Rudová, H. (2008). Alea–grid scheduling simulation environment. In *Parallel Processing and Applied Mathematics: 7th International Conference* (pp. 1029-1038). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-68111-3_109.

Lei, K., Guo, P., Zhao, W., Wang, Y., Qian, L., Meng, X., & Tang, L. (2022). A multi-action deep reinforcement learning framework for flexible job-shop scheduling problem. *Expert Systems with Applications*, *205*, 117796. https://doi.org/10.1016/j.eswa.2022.117796.

Luo, S. (2020). Dynamic scheduling for flexible job shop with new job insertions by deep reinforcement learning. *Applied Soft Computing*, *91*, 106208. https://doi.org/10.1016/j.asoc.2020.106208.

Luo, S., Zhang, L., & Fan, Y. (2021). Dynamic multi-objective scheduling for flexible job shop by deep reinforcement learning. *Computers & Industrial Engineering*, *159*, 107489. https://doi.org/10.1016/j.cie.2021.107489.

Mohanasundaram, K.M., Natarajan, K., Viswanathkumar, G., Radhakrishnan, P., & Rajendran, C. (2003). Scheduling rules for dynamic shops that manufacture multi-level jobs. *Computers & Industrial Engineering*, *44*(1), 119-131. https://doi.org/10.1016/S0360-8352(02)00188-2.

Nasiri, M.M., Yazdanparast, R., & Jolai, F. (2017). A simulation optimisation approach for real-time scheduling in an open shop environment using a composite dispatching rule. *International Journal of Computer Integrated Manufacturing*, *30*(12), 1239-1252. https://doi.org/10.1080/0951192X.2017.1307452.

Oukil, A., El-Bouri, A., & Emrouznejad, A. (2022). Energy-aware job scheduling in a multi-objective production environment – an integrated DEA-OWA model. *Computers & Industrial Engineering*, *168*, 108065. https://doi.org/10.1016/j.cie.2022.108065.

Pinciroli, L., Baraldi, P., & Zio, E. (2023). Maintenance optimization in industry 4.0. *Reliability Engineering & System Safety*, *234*, 109204. https://doi.org/10.1016/j.ress.2023.109204.

Quadras, D.L.O., Mafia, M.M.P., Mendes, L.G., Braghirolli, L.F., & Frazzon, E.M. (2024). Perspectives for the application of reinforcement learning for the integrated order-dispatching and maintenance scheduling. *IFAC-PapersOnLine*, *58*(8), 79-84. https://doi.org/10.1016/j.ifacol.2024.08.054.

Riaventin, V.N., Cakravastia, A., Cahyono, R.T., & Suprayogi. (2024). Sustainable synchronization of truck arrival and yard crane scheduling in container terminals: an agent-based simulation of centralized and decentralized approaches considering carbon emissions. *Sustainability*, *16*(22), 9743. https://doi.org/10.3390/su16229743.

Sanaj, M.S., & Prathap, P.J. (2020). An enhanced round robin (ERR) algorithm for effective and efficient task scheduling in cloud environment. In *2020 Advanced Computing and Communication Technologies for High Performance Applications* (pp. 107-110). IEEE. Cochin, India. https://doi.org/10.1109/ACCTHPA49271.2020.9213198.

Shady, S., Kaihara, T., Fujii, N., & Kokuryo, D. (2021). Evolving dispatching rules using genetic programming for multi-objective dynamic job shop scheduling with machine breakdowns. *Procedia CIRP*, *104*, 411-416. https://doi.org/10.1016/j.procir.2021.11.069.

Shi, S., Xiong, H., & Li, G. (2023). A no-tardiness job shop scheduling problem with overtime consideration and the solution approaches. *Computers & Industrial Engineering*, *178*, 109115. https://doi.org/10.1016/j.cie.2023.109115.

Smith, D., & Srinivas, S. (2019). A simulation-based evaluation of warehouse check-in strategies for improving inbound logistics operations. *Simulation Modelling Practice and Theory*, *94*, 303-320. https://doi.org/10.1016/j.simpat.2019.03.004.

Souza, R.L.C., Ghasemi, A., Saif, A., & Gharaei, A. (2022). Robust job-shop scheduling under deterministic and stochastic unavailability constraints due to preventive and corrective maintenance. *Computers & Industrial Engineering*, *168*, 108130. https://doi.org/10.1016/j.cie.2022.108130.

Teck, S., Vansteenwegen, P., & Dewil, R. (2023). An efficient multi-agent approach to order picking and robot scheduling in a robotic mobile fulfillment system. *Simulation Modelling Practice and Theory*, *127*, 102789. https://doi.org/10.1016/j.simpat.2023.102789.

Teymourifar, A., Ozturk, G., Ozturk, Z.K., & Bahadir, O. (2020). Extracting new dispatching rules for multi-objective dynamic flexible job shop scheduling with limited buffer spaces. *Cognitive Computation*, *12*, 195-205. https://doi.org/10.1007/s12559-018-9595-4.

Thenarasu, M., Rameshkumar, K., Di Mascolo, M., & Anbuudayasankar, S.P. (2024). Multi-criteria scheduling of realistic flexible job shop: a novel approach for integrating simulation modelling and multi-criteria decision making. *International Journal of Production Research*, *62*(1-2), 336-358. https://doi.org/10.1080/00207543.2023.2238084.

Torres, C., Barbieri, G., & Muñoz, M. (2024). A discrete event simulator to support maintenance decision-making considering economic and environmental sustainability. *IFAC-PapersOnLine*, *58*(8), 347-352. https://doi.org/10.1016/j.ifacol.2024.08.145.

Voskresenskii, A., Kovalchuk, M., Filatova, A., Nasonov, D., & Lutsenko, A. (2023a). Hybrid algorithm for multi-contractor, multi-resource project scheduling in the industrial field. *Procedia Computer Science*, *229*, 28-38. https://doi.org/10.1016/j.procs.2023.12.004.

Voskresenskii, A., Kovalchuk, M., Filatova, A., Nasonov, D., & Lutsenko, A. (2023b). Hybrid algorithm for multi-contractor, multi-resource project scheduling in the industrial field. *Procedia Computer Science*, *229*, 28-38. https://doi.org/10.1016/j.procs.2023.12.004.

Wang, R., Wang, G., Sun, J., Deng, F., & Chen, J. (2024). Flexible job shop scheduling via dual attention network-based reinforcement learning. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(3), 3091-3102. https://doi.org/10.1109/TNNLS.2023.3306421.

Wang, Z., & Wu, Y. (2023). An ant colony optimization-simulated annealing algorithm for solving a multiload AGVs workshop scheduling problem with limited buffer capacity. *Processes*, *11*(3), 861. https://doi.org/10.3390/pr11030861.

Wu, Z., Fan, H., Sun, Y., & Peng, M. (2023). Efficient multi-objective optimization on dynamic flexible job shop scheduling using deep reinforcement learning approach. *Processes*, *11*(7), 2018. https://doi.org/10.3390/pr11072018.

Xu, S., Li, Y., & Li, Q. (2024). A deep reinforcement learning method based on a transformer model for the flexible job shop scheduling problem. *Electronics*, *13*(18), 3696. https://doi.org/10.3390/electronics13183696.

Zeiträg, Y., & Figueira, J.R. (2023). Automatically evolving preference-based dispatching rules for multi-objective job shop scheduling. *Journal of Scheduling*, *26*(3), 289-314. https://doi.org/10.1007/s10951-023-00783-9.

Zeiträg, Y., Figueira, J.R., Horta, N., & Neves, R. (2022). Surrogate-assisted automatic evolving of dispatching rules for multi-objective dynamic job shop scheduling using genetic programming. *Expert Systems with Applications*, *209*, 118194. https://doi.org/10.1016/j.eswa.2022.118194.

Zhang, S., & Wang, S. (2018). Flexible assembly job-shop scheduling with sequence-dependent setup times and part sharing in a dynamic environment: constraint programming model, mixed-integer programming model, and dispatching rules. *IEEE Transactions on Engineering Management*, *65*(3), 487-504. https://doi.org/10.1109/TEM.2017.2785774.

Zhang, T., Li, H., Fang, Y., Luo, M., & Cao, K. (2023). Joint dispatching and cooperative trajectory planning for multiple autonomous forklifts in a warehouse: a search-and-learning-based approach. *Electronics*, *12*(18), 3820. https://doi.org/10.3390/electronics12183820.

Zhao, Y., Wang, Y., Tan, Y., Zhang, J., & Yu, H. (2021). Dynamic job-shop scheduling algorithm based on deep Q network. *IEEE Access*, *9*, 122995-123011. https://doi.org/10.1109/ACCESS.2021.3110242.