Management and Production Engineering Review
Volume 16 • Number 4 • December 2025 • pp. 1–12
DOI: 10.24425/mper.2025.157209

Pure Flow Shop m-Machine Scheduling to Minimize Job Lateness Using Dispatching Rules

Filscha NURPRIHATIN[1], Yulistia YULISTIA[2], Ester Lisnati JAYADI[3], Ivana Tita Bella WIDIWATI[1], Yogi Tri PRASETYO[4], Hendy TANNADY[5]

[1] *Department of Industrial Engineering, Sampoerna University, Indonesia*
[2] *Department of Industrial Engineering, Universitas Bunda Mulia, Indonesia*
[3] *Department of Management, Linnaeus University, Sweden*
[4] *International Bachelor Program in Engineering, Yuan Ze University, Taiwan*
[5] *Department of Postgraduate in Management, Universitas Esa Unggul, Indonesia*

Received: 09 November 2024
Accepted: 20 September 2025

Abstract
This study examines the problem of minimizing job lateness in the paper manufacturing industry, focusing on cut-size machine scheduling under fluctuating demand. Historical demand data (2018–2019) were forecast using Double Exponential Smoothing (DES) and Holt–Winters' Triple Exponential Smoothing (TES), with accuracy assessed via Mean Absolute Percentage Error (MAPE). The forecasts informed scheduling models for single- and parallel-machine environments using dispatching rules, including Earliest Due Date (EDD), Shortest Processing Time (SPT), Critical Ratio (CR), Longest Processing Time (LPT), and Least Slack Time (LST). Results show Holt–Winters' TES achieves the most accurate forecasts, while EDD consistently minimizes lateness, reducing delays by more than 70% compared with alternatives. These findings highlight the value of integrating forecasting and scheduling to enhance machine utilization and delivery performance. The framework offers practical guidance for demand planning and resource allocation in export-oriented manufacturing sectors facing high demand variability.

Keywords
Job Scheduling, lateness minimization, single-machine scheduling, parallel machine scheduling, demand forecasting.

Introduction

In Indonesia, the demand for paper continues to grow and remains essential as pulp and paper exports amounted to US$691.20 million in 2022 (Ministry of Industry of the Republic of Indonesia, 2022). However, in March 2022, the year-on-year demand for paper in Indonesia decreased by 5.14% (Ministry of Industry of the Republic of Indonesia, 2022). Nonetheless, with the expected economic recovery post-COVID-19, the demand for paper is anticipated to rebound. This growth is likely to result in increased competition among paper manufacturers, necessitating efficient and timely production processes to ensure customer satisfaction and maintain competitiveness in the market (Ervural & Ervural, 2018; Tannady et al., 2019). To address these challenges, a recent study focused on optimizing the scheduling of inbound and outbound trucks (Nurprihatin et al., 2021a), while manufacturers are also striving for faster, more reliable processes while minimizing costs (Sá et al., 2022). This paper aims to analyze the manufacturing process of a paper company in Indonesia and propose the best scheduling technique to enhance machine productivity.

This study focuses on a company within the paper industry that produces a variety of paper products, including carbonless paper, cast-coated paper, photocopy paper, tissue paper, and art paper. Through interviews with industry peers and on-site observations, it was discovered that the cut-size machine poses scheduling challenges for the Production Planning and Inventory Control (PPIC) Department. The department faces constant changes in the production schedule for the cut-size machines, making it difficult to establish a definitive schedule. The company adopts

***Corresponding author**: Filscha Nurprihatin – Department of Industrial Engineering, Sampoerna University, Indonesia, e-mail: filscha.nurprihatin@sampoernauniversity.ac.id*

a make-to-order strategy due to fluctuating demand and diverse product specifications. Make-to-order entails completing the final product only upon receiving a consumer order (Chapman et al., 2017). Despite this approach, production delays at the cut-size machine have led to challenges in meeting consumer demand.

The products resulting from the operations are sold both domestically and internationally. The majority of delays occur in international sales. Specifically, 6.97% of local demand and 69.62% of international demand were not met. The primary cause of these delays is the inadequate scheduling of the cut-size machine. Within the cut-size process, the company utilizes five machines with varying specifications. As per company policy, two machines, namely Cut Machine 2 and Cut Machine 4, are dedicated to fulfilling international orders. Cut Machine 2 can process A4, B4, B5, and A3 sizes, with a daily capacity of 200 tons, while Cut Machine 4 is limited to processing A4 paper, with a daily capacity of 100 tons. Given these differences in specifications and capacities, it is crucial to develop a scheduling technique based on forecasted demand to ensure optimal performance of the machines in meeting our customers' needs.

The central research problem lies in the company's inability to synchronize fluctuating, make-to-order demand with machine scheduling, leading to recurrent lateness in both domestic and international deliveries. Existing scheduling practices are reactive, lacking integration with demand forecasts, which results in underutilization of machine capacity and missed deadlines. While prior studies have examined forecasting or scheduling independently, there remains a gap in research that explicitly combines both to minimize job lateness in a complex, multi-machine environment. Parallel batch (p-batch) scheduling introduces grouping decisions on top of assignment and sequencing and is now a mature subfield with clear taxonomies across single/parallel machines, compatible vs. incompatible families, and flow/due date objectives (Fowler & Mönch, 2022). Within this stream, incompatible-family batching with non-identical job sizes is computationally challenging and links bin-packing with machine scheduling; recent exact and decomposition methods (time-indexed, set-partitioning with column generation, and branch-and-price) achieve state-of-the-art performance for weighted completion time on a single parallel-batching machine (Yang et al., 2022). This study addresses that gap by linking quantitative demand forecasting with systematic scheduling rules to create a proactive decision-making framework.

In the era of the new industrial revolution, manufacturers are required to offer comprehensive solutions to add value in terms of products and services (Luo et al., 2022). This study aims to identify the most accurate forecasting method to ensure timely production and high quality. Forecasting is an advanced way of estimation that considers the production system to be efficient (Hartner & Mezhuyev, 2022). Past data analysis is taken into consideration to get an estimation of future events (Deckert et al., 2022). A very effective way to win a competitive advantage in business is for companies to have smooth production processes that are on schedule, eliminating delays and issues. Delivery of customer-demanded products at the proper time leads to customer satisfaction. Therefore, a good scheduling policy is crucial to planning and organizing production according to customers' demands. The novelty of this approach is in its dual focus: first, identifying the most accurate forecasting method for capturing demand seasonality and trend, and second, empirically testing dispatching rules to determine which minimizes lateness across single and parallel machines. By integrating these two stages, the study directly responds to the company's operational problem of delivery delays and provides a generalizable framework for industries with volatile demand. This scheduling effect will enable better delivery schedules and also help in increasing customer service (Heizer et al., 2020). Whereas state-of-the-art exact methods address single parallel-batching machines with incompatible families, we extend the modeling and algorithmic toolkit to multiple machines with pure flow shop environment, showing scalability while preserving solution quality (Fowler & Mönch, 2022; Yang et al., 2022). These advances are directly applicable to semiconductor and electronics (furnace and metrology batching), healthcare sterilization, and platform logistics where delivery commitments are integral, aligning with the usage contexts synthesized by recent surveys.

Literature review

Many previous studies had forecasted using Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt–Winters' Triple Exponential Smoothing (TES) (Nurprihatin et al., 2020 2022, 2023; Nurprihatin et al., 2021b). Because of their efficiency and simplicity with quite good accuracy, exponential smoothing methods are considered an important quantitative method in forecasting (Khairina et al., 2021). Selection of appropriate exponential methods should consider the characteristics of the data in concern and the correlation between the variables. DES is more effective in analyzing the trend pattern (Peng et al., 2015). However, non-linear correlation between independent and dependent variables can be utilized optimally to forecast the data by Holt–Winters' TES (Peng et al., 2015). Hence, these methods will be discussed further in this study to identify an appropriate and accurate approach to the forecast. Table 1 shows the three studies related to exponential smoothing. Such articles and this research all belong to the same purpose-that is, to forecast and then enable the company to be more reliable.

One study employed the DES method for a stream processing platform in a distribution (Wang et al., 2018). The DES applied to one scheduling algorithm showed outstanding performance regarding network topology, load balancing of tasks, and processing time (Wang et al., 2018). Apart from that, one forecasting study was conducted for smart transportation planning to develop sustainable and intelligent transportation systems (Karami & Kashef, 2020). In this regard, machine learning methods utilized the Holt–Winters TES-and these have been tested to be very efficient in forecasting seasonal and trend data (Karami & Kashef, 2020). Another study on exponential smoothing was to analyze the river flow pattern and condition, and the study proved that Holt–Winters' TES is a more precise way of forecasting because the error values are smaller compared with other SES, DES, and ARIMA (Lukman & Tanan, 2021).

Scheduling will be done based on the forecasting results, ensuring the cutting machine operates efficiently to meet the predicted demand. Scheduling can be defined as the preparation of a sequence of manufacturing or work processes of a product through several machines. Beyond factory-floor processing, distributed manufacturing emphasizes the coupling of shop scheduling with delivery/transport decisions. Recent work formalizes this by minimizing total weighted delivery time (TWD) on parallel machines, introducing job- and machine-dependent delivery durations

Table 1
Literature Review

Authors	**Forecasting Method**		**Dispatching Rules**					**Objectives**
	DES	Holt–Winters' TES	EDD	SPT	LST	CR	LPT	
Wang et al., 2018	✓							Proposing an on-the-fly scheduling strategy through Double Exponential Smoothing (DES) to adjust routing and balance the inter-worker load
Karami & Kashef, 2020		✓						Presenting the advantages and drawbacks of various machine learning models
Lukman & Tanan, 2021	✓	✓						Analyzing four exponential smoothing techniques to predict a river flow.
Lödding & Piontek, 2017			✓					Analyzing the EDD's effectiveness in a make-to-order production schedule
Dell'Amico, 2019				✓				Evaluating the SPT method through simulation to prove the merits of this method when it is implemented for inexact job size scheduling
Silva et al., 2018					✓			Proposing a smart energy management system with load balancing and a scheduling algorithm
Zhao et al., 2021				✓	✓	✓	✓	Improving the DQN-based adaptive scheduling performance of a dynamic production process environment.
Tyagi et al., 2016			✓		✓		✓	Overcoming scheduling problems to solve a delay problem
This paper	✓	✓	✓	✓	✓	✓	✓	Determining the best forecasting method and minimizing tardiness through scheduling

and effective GRASP-based solution frameworks that outperform genetic-algorithm baselines on small and large (Mönch & Shen, 2021). Various issues that occur in scheduling include the time required for processing, completion time, due date, and setup time (Roychowdhury et al., 2017). Effective and dynamic scheduling has a positive effect on cost savings and allows the processing of applications at a large scale (Zhou et al., 2019). Another study proposed preventive maintenance incorporated in production scheduling (Assia et al., 2020). This paper divides scheduling into two categories: n-job for a single machine and n-job for m-machines. Each category uses different dispatching rules, which are discussed in detail to conclude the most efficient approach. The dispatching rules used in this paper are: Earliest Due Date (EDD), Shortest Processing Time (SPT), Least Slack Time (LST), Critical Ratio (CR), and Longest Processing Time (LPT).

While in previous work a detailed investigation has been performed regarding the effectiveness of EDD's scheduling in a make-to-order production process, it could be shown that the utilization of an intuitively reasonable dispatching rule allows for an improved schedule conformity, where always the first scheduled order is being processed (Lödding & Piontek, 2017). Another work examined the use of the SPT rule to make use of its advantages regarding inexact job scheduling (Dell'Amico, 2019). The findings indicated that SPT performs optimally in the presence of errors, and its simplification can lead to further analytical evaluation when dealing with inexact inputs (Dell'Amico, 2019). Moreover, dispatching rules can extend beyond the manufacturing floor. For instance, a study proposed an LST-based energy management system, demonstrating significant improvements in cost and energy consumption for the management system (Dell'Amico, 2019).

A study dealt with the problem of the Dynamic Job Shop Scheduling Problem using the Deep Q-Network algorithm (Zhao et al., 2021). It was concluded that better scheduling performance may be achieved when several dispatching rule positions cooperate in contrast to a single indicator (Zhao et al., 2021). Several dispatching rules may allow enterprises to adapt to various scheduling times and production states, thereby providing optimal scheduling outcomes. Another study focused on minimizing tardiness with different dispatching rules, which comprised SPT, EDD, LPT, LST, and FCFS (Tyagi et al., 2016). The results showed that these diverse dispatching rules have different outcomes concerning process efficiency, highlighting the SPT rule for how it reduced makespan; the EDD rule was found to be the best for minimizing tardiness (Tyagi et al., 2016).

Materials & Methods

The paper presents a case study of the base paper used for paper and wrappers in a "Top Quality Paper" manufacturing company in Indonesia. The study aims to identify the causes of delays that may occur in the base paper reaching the cut and wrapper machine. Figure 1 illustrates the steps taken to address the identified issue. To address these problems, the study formulates an approach that couples quantitative demand forecasting with rule-based scheduling. Forecasting methods (DES and Holt–Winters' TES) are employed to capture trend and seasonality in export demand, while dispatching rules (EDD, SPT, CR, LPT, LST) are systematically tested to identify the most effective scheduling strategy. This combined framework directly targets the reduction of job lateness at both single-machine and multi-machine levels.

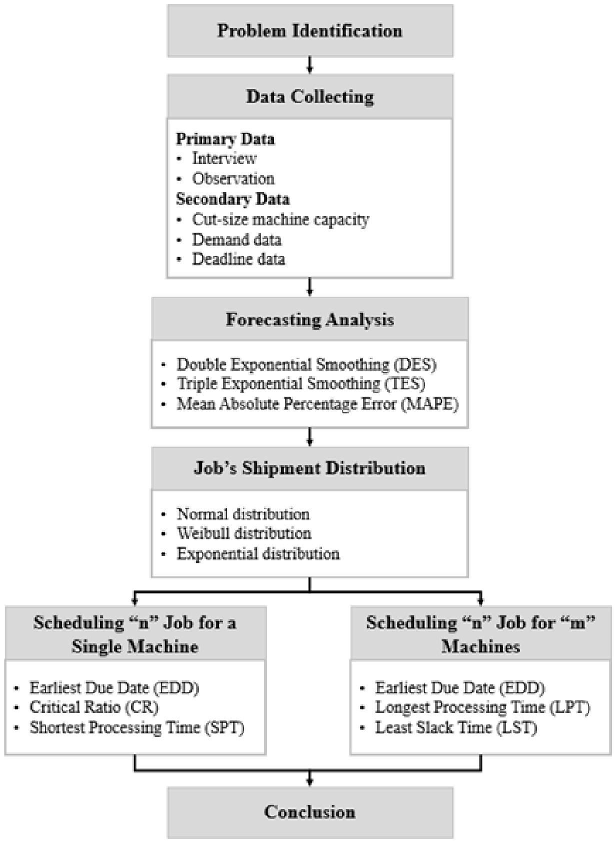

Fig. 1. Research Methodology

The research starts with observations at PPIC Uncoated PM 8/9 to identify production process issues. It involves collecting primary and secondary data, including demand, deadline, and cut-size machine capacity data. Demand forecasting is conducted using Double Exponential Smoothing (DES) and Holt–Winters' TES methods, with the accuracy of each technique assessed using Mean Absolute Percentage Error (MAPE). The best forecasting method is then used to distribute job shipments using normal, Weibull, and exponential distributions. The distribution results are used to determine paper delivery times for each paper size. Subsequently, a scheduling analysis is performed.

The scheduling analysis is segmented into two main categories: n-jobs for a single machine and n-jobs for m-machines. In the first category, the scheduling method utilizes the EDD, CR, and SPT rules. The EDD rule is also employed for the n-job for m-machines scheduling. Additionally, the LPT and LST rules are applied. In each category, the makespan will be compared to determine which one yields the best results. Finally, a conclusion will be drawn, and recommendations will be provided for further research and the company.

Results and Discussion

Forecasting Result

The study discusses demand forecasting for the upcoming 12 periods, from January 2020 to December 2020, using historical data on export paper demand from January 2019 to December 2019. The forecasting methods employed were Double Exponential Smoothing and Holt–Winters' TES, which consider trend lines and seasonality (Nahmias & Olsen, 2021). Holt–Winters' TES is chosen as the best forecasting method, with different values of α, β, and γ for each paper size, as described in Table 2. The forecasting results for 2020 are presented in Table 3.

Table 2
Holt–Winters' TES Parameter

Paper Size	Holt–Winters' TES Parameter
A3	$\alpha = 0.6$, $\beta = 0.7$, $\gamma = 0.8$
A4	$\alpha = 0.6$, $\beta = 0.7$, $\gamma = 0.8$
B4	$\alpha = 0.7$, $\beta = 0.8$, $\gamma = 0.9$
B5	$\alpha = 0.6$, $\beta = 0.7$, $\gamma = 0.8$

The empirical patterns show that forecasting accuracy (Holt–Winters TES) reduces uncertainty in job arrivals, and that EDD minimizes sequencing lateness. This echo application domains identified in the p-batch literature (e.g., semiconductor testing, hospital sterilization, platform manufacturing) (Fowler & Mönch, 2022). This convergence indicates our findings

Table 3
Forecasting Results in 2020

No	Month	Demand Forecast (kg)			
		A3	A4	B4	B5
1	January	432540	7844772	249645	24007.7
2	February	617447	11229840	110176	54331.8
3	March	660204	10186625	142946	21990.7
4	April	550149	8610162	197556	22382.3
5	May	431450	8769472	78338	939.7
6	June	855007	7541804	194319	84.2
7	July	406794	6440700	131883	13625.1
8	August	580326	5244095	300047	9575.3
9	September	620110	7321875	199651	40650.5
10	October	516397	6456245	346557	29250.2
11	November	404708	5283031	151177	55793.8
12	December	801457	5182785	194031	5611.2

have direct transferability to contexts where batching decisions and international delivery commitments co-exist (Yang et al., 2022), adopting forecast-aware scheduling can materially improve on-time performance in export-oriented production systems.

Job's Shipment Distribution

The data distribution is assessed using Minitab 16 software. The distribution method is chosen based on either the Anderson-Darling value or the p-value. The smallest Anderson-Darling value or the most significant p-value should be selected. This data distribution calculation is utilized for forecasting delivery schedules.

The data in Table 4 illustrates the frequency of shipments for each size category. Each month, A3 shipments occur every 11 days, while A4 shipments occur every 7 days. On the other hand, B4 and B5 are shipped together every 22 days each month. To clarify, A3 and A4 are shipped 1 to 3 times and 4 to 5 times a month, respectively. Meanwhile, B4 and B5 each have 1 or 2 deliveries per month.

Table 4
Job's Shipment Data Distribution

Size	Distribution	Mean (days)
A3	Weibull	$10.97 \approx 11$

Scheduling n-Jobs Single-Machine

From an algorithmic perspective, the literature reveals a spectrum from exact approaches that scale to medium-sized instances, to fast heuristics and metaheuristics for industry scales. A previous study demonstrated that set-partitioning/branch-and-price formulations can solve single p-batch instances to optimality up to moderate sizes, while recent work on parallel approximation and scalable heuristics provides alternatives for large, dynamic shop-floor problems (Badri et al., 2021; Yang et al., 2022). Our choice to evaluate rule-based dispatching (EDD, SPT, CR, LPT, LST) therefore aligns with the practical need for fast, interpretable rules, but also suggests that computational resources and data permit could improve solution quality.

1. Shortest Processing Time (SPT)
   The SPT method involves arranging jobs in order of shortest to longest total job processing time each month. Once the jobs are sorted, the next step is to calculate lateness, average completion time, average number of jobs, and makespan for each month. Table 5 provides the job sequencing using SPT.
2. Earliest Due Date (EDD)
   Scheduling with the EDD method can help minimize lateness when using a single processor. The EDD theory involves sorting jobs from the shortest to the longest due date, with the job having the earliest due date taking precedence. Refer to Table 6 for the job sequencing using EDD. The scheduling results presented here resonate with the broader parallel-batch (p-batch) literature, showing that grouping decisions materially affect delivery performance and in-process inventory. A recent survey highlights how p-batch models combine grouping, assignment, and sequencing decisions and that objective choice (flow time, makespan, tardiness) substantially alters algorithmic recommendations (Fowler & Mönch, 2022), while our emphasis on lateness minimization therefore fits squarely within this emerging taxonomy.
3. Critical Ratio (CR)
   In CR theory, the job is prioritized based on the job with the smallest CR value. The CR value is calculated and then sorted from smallest to largest. Table 7 illustrates the job sequencing using CR.
   A comparison of the results for single-machine scheduling using SPT, EDD, and CR indicates that EDD is the most suitable schedule as it does not result in any lateness.

Scheduling n-Job m-Parallel Machine

1. Longest Processing Time (LPT)
   The LPT theory is designed to minimize lateness and shorten the makespan. According to this theory, all jobs are sorted from the longest processing

Table 5
Job Sequence Using SPT (Single-Machine)

Month	Sequence	Job Lateness (days)	Makespan (days)
1	1-2-14-15-9-3-10-16-11-4-17-12-13-18-7-5-6-19-8	0.21	3.52
2	5-8-9-1-10-11-6-12-13-14-15-7-3-16-17-18-19-20-21-2-4-22-	0.00	3.87
3	3-7-8-9-10-11-5-2-12-6-13-14-15-16-1-17-4-18	0.00	4.04
4	10-11-12-13-14-15-2-9-16-17-18-19-20-21-22-3-4-23-5-24-1-25-6-7-8	0.00	2.31
5	14-15-8-9-16-17-18-19-20-21-22-5-1-2-10-11-23-12-6-4-7-13-3-	0.13	5.09
6	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16	0.00	5.25
7	4-5-6-7-8-9-10-11-12-13-3-14-15-16-17-18-1-2-19	0.00	2.76
8	6-7-3-5-8-9-10-11-12-1-13-14-15-2-4-16-17	0.00	4.45
9	2-3-4-1-5-6-7-8-9	0.00	4.30
10	4-10-11-12-5-13-6-7-14-1-8-15-16-2-17-18-3-9-19	0.00	4.41
11	2-3-7-4-9-10-5-8-11-12-13-14-15-16-17-1-6	0.00	3.05
12	5-1-6-7-8-9-10-3-11-12-13-14-15-16-17-2-4-18-19	0.00	5.01

Table 6
Job Sequence Using EDD (Single-Machine)

Month	Sequence	Job Lateness (days)	Makespan (days)
1	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19	0.00	3.52
2	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22	0.00	3.87
3	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18	0.00	4.04
4	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25	0.00	2.31
5	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23	0.00	5.09
6	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16	0.00	5.25
7	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19	0.00	2.76
8	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17	0.00	4.45
9	1-2-3-4-5-6-7-8-9	0.00	4.30
10	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19	0.00	4.41
11	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17	0.00	3.05
12	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19	0.00	5.01

Table 7
Job Sequence Using CR (Single-Machine)

Month	Sequence	Job Lateness (days)	Makespan (days)
1	7-14-3-5-8-16-9-10-15-1-4-12-19-13-11-17-2-18-6	0.00	3.52
2	2-4-14-16-1-21-18-19-8-13-5-9-11-10-17-6-15-20-12-7-22	0.05	3.87
3	14-3-1-7-2-8-12-6-9-11-5-16-18-17-13-15-4-10	0.00	4.04
4	1-3-6-4-10-5-12-7-8-14-15-16-20-2-17-19-13-18-9-11-21-24-23-22-25	0.00	2.31
5	3-4-8-1-7-5-2-11-9-10-14-6-20–17-21-16-19-18-15-12-13-22-23	0.00	5.09
6	6-3-10-8-4-2-5-1-12-7-11-9-14-15-16-13	0.00	5.25
7	1-2-13-4-10-11-3-7-6-5-17-14-8-12-15-9-16-18-19	0.00	2.76
8	2-11-14-3-1-15-13-9-10-8-6-17-4-12-5-7-16	0.00	4.45
9	3-2-8-1-5-6-9-4-7	0.00	4.30
10	2-3-9-12-1–6-5-15-17-11-7-18-14-8-13-19-4-16-10	0.00	4.41
11	1-6-9-12-13-17-3-14-15-8-16-11-4-2-10-7-5	0.00	3.05
12	2-4-12-16-14-15-3-6-7-10-9-5-17-1-8-18-13-11-19	0.00	5.01

time to the shortest. After obtaining the results, the jobs with the longest processing time on each machine are then sorted according to the shortest processing time rules. Subsequently, the order of the jobs on each machine is reversed based on the shortest processing time rules. Table 8 provides a visual representation of the job sequencing according to LPT.

2. Least Slack Time (LST)
LST is used to reduce the lateness of parallel machines. The slack time refers to the time gap between the completion time of task i and its associated due date, as shown in Equation 1. The job sequencing using LST is explained in Table 9.

$$\text{LST} = \text{Due Date} - \text{Processing Time} \tag{1}$$

Table 8
Job Sequence Using LPT (m-Parallel Machines)

Month	Sequence		Makespan (days)		Job Lateness (days)
	M2	M4	M2	M4	
1	17-10-12-6-27-23-8-4-7-20-13-21-18-14-5-2	1-22-15-9-3-19-26-11-24-16-25	34.70	34.68	0.56
2	4-2-12-9-7-16-13-18-1-5-3-10	18-6-14-17-15-11	21.29	21.19	0.00
3	10-6-7-1-21-9-23-11-14-20-8-5-2	16-4-3-15-17-18-13-12-22-19	33.41	33.43	1.96
4	29-7-18-20-19-11-21-14-13-26-15-8-16-1-5	4-3-25-22-27-9-23-17-12-10-28-2-24	29.55	29.47	0.86
5	25-8-1-9-10-3-27-12-26-14-2-11-22	21-18-4-20-5-7-15-13-19-16-17-6-24-23	28.96	29.14	0.41
6	7-2-21-18-22-14-1-20-10-8-15-6-3	23-11-4-17-12-16-5-19-13-9	28.15	28.13	0.74
7	17-5-6-19-23-18-12-14-11-3-2-23-7-20	10-15-1-4-22-26-21-16-25-13–9-8	28.00	28.05	0.00
8	17-8-11-19-26-9-18-23-2-1-10-4-7-14-22	13-16-12-20-6-24-3-21-25-5-15	20.72	20.79	0.00
9	2-12-21-1-24-22-4-15-9-8-5-3-13	6-16-20-11-23-14-10-7-19-17-18	33.05	33.15	1.29
10	24-11-14-5-8-13-1-30-15-4-19-26-23-28-10-3-20	21-27-9-12-2-7-16-6-22-18-17-29-25	20.13	20.13	0.27
11	27-1-4-16-30-20-34-32-11-21-17-25-14-28-13-8-2-10-5	12-7-31-9-24-15-22-26-3-6-23-33-19-18-29	32.35	32.29	1.53
12	29-30-20-6-11-22-23-15-28-24-32-33-8-2-10-4-31-7-16-17-9-3-1-19-13	21-12-26-18-25-14-5-27	29.42	29.44	0.91

Table 9
Job Sequence Using LST (m-Parallel Machines)

Month	Sequence		Makespan (days)		Job Lateness (days)
	M2	M4	M2	M4	
1	25-13-20-23-27-17	2-3-1-5-7-4-6-8-910-14-18-11-21-16-24-12-15-26-19-22	34.75	34.63	1.74
2	1-2-4-11-14-18	3-5-6-10-8-13-15-16-7-17-9-12	21.20	21.28	0.00
3	1-3-19-14-11-13-17-15	2-5-4-8-6-9-7-10-20-22-12-23-18-21	33.27	33.36	1.14
4	2-3-24-7-16-11-15-26-13-21-22-25-20	1-5-8-9-6-4-10-28-12-17-23-14-27-19-18-29	29.43	29.60	0.00
5	3-1–6-11-9-22-14-17-16-13-18-25-21	2-4-7-5-8-12-10-23-24-26-19-27-15-20	29.08	29.02	0.00
6	9-10-20-22-12-21-7	3-1-2-4-6-5-15-8-13-14-16-18-17-11-23	28.14	28.14	0.00
7	1-8-5-9-13-25-16-18-23-22-17-15	2-3-4-20-7-24-11-14-12-21-26-19-6-10	28.02	28.03	0.00
8	2-4-5-3-7-6-8-10-9-14-11-12-17-16-13-18-19-20-21-22	1-15-23-24-25-26	21.28	20.23	0.00
9	1-18-9-19-10-14-23-11-20-16	3-4-2-5-7-6-8-13-17-15-22-24-21-12	33.37	32.84	0.83
10	1-4-2-10-13-12-11-20-14-28-23-26-29-19-17-18-15-22-24	3-6-5-8-7-9-25-30-16-27-21	20.13	20.14	0.00
11	3-1-29-18-19-17-23-32-34-20-22-15-24	2-5-8-6-4-7-10-13-11-9-12-28-14-25-33-21-26-30-16-31-27	32.25	32.40	0.91
12	1-3-7-4-2-5-6-9-10-8-11-13-19-17-16-31-12-32-24-28-15-23-14-18-26-29-33	27-22-25-20-30-21	29.91	28.95	0.00

Earliest Due Date (EDD)

The job sequencing using the Earliest Due Date (EDD) method is presented in Table 10.

In a multi-parallel machine environment, it has been observed that implementing both the EDD and the LST methods can effectively minimize lateness over the course of 12 months. The EDD method resulted in 8 instances of lateness, with an average lateness of 2.25 days or 54 hours. Similarly, the LST method also resulted in 8 instances of lateness, with an average lateness of 4.62 days or 110.88 hours.

Our finding that EDD yields zero lateness in the single-machine case aligns with empirical evidence that carefully chosen sequencing rules outperform naïve heuristics when batching structure and job incompatibilities are limited. Recent exact and column-generation methods for single p-batch problems with non-identical job sizes demonstrate that exploiting problem structure (family compatibility, capacity constraints) substantially narrows the performance gap between heuristics and optimal solutions (Yang et al., 2022). In our setting, the relative simplicity of due-date ordering captures the dominant constraint, which explains why EDD performs close to the reported optimal heuristics in similar studies.

The remaining tardiness under multi-machine dispatching echoes the evidence that single-machine prioritization rules often degrade when machines are heterogeneous or subject to sequence-dependent setups. Recent empirical work shows that the Apparent Tardiness Cost (ATC)-type rules extended to account for machine efficiencies and ready/setup times can significantly reduce weighted tardiness in parallel settings (Wu et al., 2024). This suggests that augmenting EDD with machine-aware ATC adjustments (or adopting the new dispatching variants recently proposed) could further close the gap in our m-machine scenarios (Wu et al., 2024).

Conclusions

This study makes three distinct contributions to the scheduling and forecasting literature. First, it demonstrates the integration of demand forecasting methods

Table 10
Job Sequence Using EDD (m-Parallel Machines)

Month	Sequence		Makespan (days)		Job Lateness (days)
	M2	M4	M2	M4	
1	2-6-7-9-10-12-13-15-16-17-18-22-23-24-25	1-3-4-5-8-11-14-19-20-21-26-27	47.56	21.82	0.67
2	2-3-6-7-8-11	1-4-5-9-10-12-13-14-15-16-17-18	25.15	17.33	0.00
3	2-6-7-8-13-1-16-17-18-19	1-3-4-5-9-10-11-12-14-20-21-22-23	39.97	26.86	0.00
4	2-4-5-16-21-24	1-3-6-7-8-9-10-11-12-13-14-15-17-18-19-20-22-23-25-26-27-28-29	32.94	26.09	0.00
5	2-7-8-9-10-12-13-14-16-18-19-20-21-23	1-3-4-5-6-11-15-17-22-24-25-26-27	37.08	31.53	0.46
6	2-3-7-8-10-11-12-13-14-15-16-17-18-19-20-21-22-23	1-4-5-6-9	26.73	29.55	0.00
7	2-4-6-8-24	1-3-5-7-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-25-26	29.46	26.60	0.00
8	2-4-6-8-9-10-11-13-15	1-3-5-7-14-16-17-18-19-20-21-22-23-24-25-26	22.39	19.12	0.00
9	2-3-6-7-8-10-14-15-16-17-18	1-4-5-9-11-12-13-19-20-21-22-23-24	40.55	25.65	0.46
10	2-3-10-18-20-26-27-28-29-30	1-4-5-6-7-8-9-11-12-13-14-15-16-17-19-21-22-23-24-25	16.74	23.53	0.00
11	2-6-7-8-11-12-13-15-16-17-19-20-21-23-26-27-28-30-31-32-33-34	1-3-4-5-9-10-14-18-22-24-25-29	23.90	40.74	0.32
12	2-3-5-7-10-11-13-17-20-21-22-24-26-28-29-30-31-32-33	1-4-6-8-9-12-14-15-16-18-19-23-25-27	18.33	40.53	0.33

(DES and Holt–Winters' TES) with scheduling rules (EDD, SPT, CR, LPT, LST) in a real industrial context, where an approach is rarely implemented jointly in empirical case studies. Second, it provides empirical validation that Holt–Winters' TES significantly reduces forecasting error, while EDD consistently minimizes lateness across both single-machine and parallel-machine environments. Third, under the condition that these findings within the paper manufacturing sector, the research extends the external validity of scheduling heuristics beyond traditional semiconductor or healthcare sterilization contexts, thereby broadening their applicability to export-driven manufacturing industries.

In the current uncertain business environment, enterprises are compelled to seek competitive advantages to survive (Gai et al., 2022). The focus of this research is the enhancement of process efficiency through the reduction of job lateness. The two chosen methods for this research model are DES and Holt–Winters' TES, which consider trendlines and seasonality. This paper adapts different combinations of forecasting variables-smoothing constant α, trend β, and seasonality γ to derive the best method. Minimum MAPE forecasting results of every type of paper are selected. By resolving the dual problems of unreliable demand forecasts and inefficient scheduling, the research provides an operational roadmap for paper manufacturers. Specifically, it demonstrates how forecasting accuracy can reduce uncertainty in job allocation, while EDD scheduling minimizes lateness across machine environments. Together, these solutions directly mitigate the root causes of delivery delays that previously hampered the company's competitiveness. It is concluded that Holt–Winters' TES provides the minimum MAPE for every type of product. Specifically, for A3, A4, and B5 paper types, it is recommended to set the Holt–Winters' TES values of $\alpha = 0.6$, $\beta = 0.7$, and $\gamma = 0.8$ for its calculations. However, for the B4 paper, the company should set $\alpha = 0.7$, $\beta = 0.8$, and $\gamma = 0.9$ for optimal forecasting results.

The analysis of scheduling for n-jobs on a single machine indicates that the EDD method generates the optimal schedule without any tardiness. In contrast, both SPT and CR scheduling result in lateness. Over 12 months, the SPT and CR scheduling methods yield 8.16 and 1.2 hours of tardiness, respectively. Specifically, the SPT method leads to lateness in January (0.21 days) and May (0.13 days), totaling 0.34 days of lateness for the year. For CR scheduling, lateness is observed in February, resulting in 0.05 days of tardiness over 12 months.

All dispatching rules introduce some delays for the n-jobs scheduling for m-machines. However, the EDD rule incurs the lowest delay compared to the LPT and the LST rule. With LPT scheduling, lateness occurs every month except February, July, and August. The total lateness under LPT scheduling amounts to 8.53 days, equivalent to 204.72 hours in a year. The LST method results in delays in January, March, September, and November schedules, with a total lateness of 110.88 hours or 4.62 days. Notably, the EDD method exhibits the least tardiness. In this method, lateness is observed in January, May, September, November, and December, totaling 2.24 days (53.76 hours) of tardiness over a year.

The results of this study have important implications for managerial decision-making in both forecasting and scheduling. The identification of Holt–Winters' TES as the most accurate forecasting method, especially when using specific smoothing constants for different paper types, offers a solid foundation for managers to optimize their inventory and production planning. By implementing these customized forecasting models, organizations can minimize forecast errors (as measured by MAPE), leading to improved demand planning, fewer stockouts, and increased customer satisfaction. Results demonstrate when batching intensity should be increased (inventory-sensitive regimes) versus when delivery-aware sequencing dominates (service-level regimes), offering implementable policies for distributed manufacturing networks (Mönch & Shen, 2021). This efficiency can also reduce operational costs related to excess inventory or rushed orders.

Despite its practical contributions, this study has several limitations. The analysis relies on historical demand and assumes that forecast error distributions remain stable over time, which may not hold under extreme demand shocks or structural breaks. Additionally, the scheduling evaluation is limited to a fixed set of dispatching rules; more advanced methods or machine-learning-based approaches could potentially outperform EDD under highly volatile or heterogeneous machine settings. Finally, the case-study design, while rich in contextual detail, may limit the generalizability of the results across different industries without further comparative testing.

In the realm of scheduling, the EDD method has demonstrated its effectiveness in minimizing job sequencing delays. To the managers, the application of the EDD rule in single-machine scheduling means quite large savings in job delays since projects are completed in due time and keeping the company competitive. The comparison of job lateness under SPT, CR, LPT, and LST scheduling outlines the fact that the best scheduling rule is quite situational. Thus, it allows managers to optimize operational efficiency, reducing machine idle time and improving the job throughput, and ultimately results in better resource utilization with reduced costs.

This study also shows the effectiveness of Holt–Winters' TES in forecasting and the EDD rule in scheduling. Further research orientation might take several directions: First, the most useful extension would be to carry this study into other product types and other industries for general validation of findings. It would also be important to determine whether similar levels of forecasting accuracy and scheduling efficiency can be achieved in industries with either the most complicated productions or highly variable demands. Furthermore, some advanced machine learning techniques might be useful in offering new forecasting insights, particularly regarding the comparison between emerging technologies against more conventional approaches like Holt–Winters' TES and DES.

Further research may be directed at multi-machine or, even more generally, into the job shop environment to investigate whether EDD retains the championship for other conditions too. Research on hybrid dispatching rules, or on heuristic scheduling that utilizes real-time information, may deliver the more flexible approaches that are called the dynamic manufacturing setting. This would make the methods much stronger for all considerations related to exogenous factors like supply chain disruption and demand volatility during these unforeseeable times.

References

Assia, S., Ikram, E.A., Abdellah, E.B., Moumen, D., & Ahmed, E.B. (2020). A genetic algorithm and b&b algorithm for integrated production scheduling, preventive and corrective maintenance to save energy. *Management and Production Engineering Review*, *11*(4), 138–148. DOI: 10.24425/mper.2020.136128

Badri, H., Bahreini, T., & Grosu, D. (2021). A parallel randomized approximation algorithm for non-preemptive single machine scheduling with release dates and delivery times. *Computers and Operations Research*, *130*, 1–9. DOI: 10.1016/j.cor.2021.105238

Chapman, S., Arnold, T., Gatewood, A., & Clive, L. (2017). *Introduction to materials management* (8th ed.). Pearson Education Limited.

Deckert, C., Keszler, J., Schmitz, H., & Mohya, A. (2022). Working papers in industrial engineering forecasting game: teaching prospective engineers quantitative forecasting techniques with a simulation game. *Hochschule Düsseldorf Opus*, *Working Pa*(5), 43–81. DOI: https://doi.org/10.20385/opus4-3905

Dell'Amico, M. (2019, July 10). *Scheduling with inexact job sizes: the merits of shortest processing time first.* DOI: https://doi.org/10.48550/arXiv.1907.04824

Ervural, B.C., & Ervural, B. (2018). *Overview of cyber security in the industry 4.0 era* (pp. 267–284). DOI: 10.1007/978-3-319-57870-5_16

Fowler, J.W., & Mönch, L. (2022). A survey of scheduling with parallel batch (p-batch) processing. *European Journal of Operational Research*, *298*(1), 1–24. DOI: 10.1016/j.ejor.2021.06.012

Gai, Y., Yin, Y., Tang, J. and Liu, S. (2022). Minimizing makespan of a production batch within concurrent systems: Seru production perspective. *Journal of Management Science and Engineering*, 7(1), pp. 1–18. DOI: 10.1016/j.jmse.2020.10.002

Hartner, R., & Mezhuyev, V. (2022). Time series sased forecasting methods in production systems: a systematic literature review. *International Journal of Industrial Engineering and Management*, *13*(2), 119–134. DOI: 10.24867/IJIEM-2022-2-306

Heizer, J., Render, B., & Munson, C. (2020). *Operations management: sustainability and supply chain management* (13th ed.). Pearson.

Karami, Z., & Kashef, R. (2020). Smart transportation planning: data, models, and algorithms. *Transportation Engineering*, *2*, 100013. DOI: 10.1016/j.treng.2020.100013

Khairina, D.M., Daniel, Y., & Widagdo, P.P. (2021). Comparison of double exponential smoothing and triple exponential smoothing methods in predicting income of local water company. *Journal of Physics: Conference Series*, *1943*(1). DOI: 10.1088/1742-6596/1943/1/012102

Lödding, H., & Piontek, A. (2017). The surprising effectiveness of earliest operation due-date sequencing. *Production Planning & Control*, *28*(5), 459–471. DOI: 10.1080/09537287.2017.1302616

Lukman, M., & Tanan, B. (2021). Time series modeling by using exponential smoothing technique for river flow discharge forecasting (case study: Cabenge, Walanae, and Cenranae rivers system). *IOP Conference Series: Materials Science and Engineering*, *1088*(1). DOI: 10.1088/1757-899X/1088/1/012100

Luo, J., Yang, Z., Zhang, Q., & Pan, R. (2022). Service outsourcing strategy decision for value creation in manufacturing firms. *Journal of Management Science and Engineering*, *7*(2), 365–386. DOI: 10.1016/j.jmse.2021.09.007

Ministry of Industry of the Republic of Indonesia. (2022). *Executive summary of export and import development of non-oil and gas, processing industry, March 2022.* https://kemenperin.go.id/download/27846/Laporan-Ekspor-Impor-Hasil-Pengolahan-2022-Maret

Mönch, L., & Shen, L. (2021). Parallel machine scheduling with the total weighted delivery time performance measure in distributed manufacturing. *Computers and Operations Research*, *127*, 1–17. DOI: 10.1016/j.cor.2020.105126

Nahmias, S., & Olsen, T. L. (2021). *Production & operation analytics* (8th ed.). Waveland Press Inc.

Nurprihatin, F., Djajasoepena, R., Vargas, V.B., Machado, M., Junior, C., & Vaezi, A. (2023). Inventory lotsizing decisions for material requirements planning to minimize inventory costs. *Journal of Industrial Engineering*, *16*(2), 28–38.

Nurprihatin, F., Elvina, Rembulan, G. D., Christianto, K., & Hartono, H. (2021). Decision support system for truck scheduling in logistic network through cross-docking strategy. *Journal of Physics: Conference Series*, *1811*(1), 012009. DOI: 10.1088/1742-6596/1811/1/012009

Nurprihatin, F., Gotami, M., & Rembulan, G.D. (2021). Improving the performance of planning and controlling raw material inventory in food industry. *International Journal of Research in Industrial Engineering*, *10*(4), 332–345. DOI: 10.22105/riej.2021.306872.1250

Nurprihatin, F., Jayadi, E.L., & Tannady, H. (2020). Comparing heuristic methods' performance for pure flow shop scheduling under certain and uncertain demand. *Management and Production Engineering Review*, *11*(2), 50–61. DOI: 10.24425/mper.2020.133728

Nurprihatin, F., Rembulan, F.D., & Pratama, Y.D. (2022). Comparing probabilistic economic order quantity and periodic order quantity model performance under lumpy demand environment. *Management and Production Engineering Review*, *13*(4), 16–25. DOI: 10.24425/mper.2022.142391

Peng, Z., Yu, Z., Wang, H., & Yang, S. (2015). Research on industrialization of electric vehicles with its demand forecast using exponential smoothing method. *Journal of Industrial Engineering and Management*, *8*(2), 365–382. DOI: 10.3926/jiem.1287

Roychowdhury, S., Allen, T.T., & Allen, N.B. (2017). A genetic algorithm with an earliest due date encoding for scheduling automotive stamping operations. *Computers & Industrial Engineering*, *105*, 201–209. DOI: 10.1016/j.cie.2017.01.007

Sá, S., Ferreira, L.P., Silva, F.J.G., Sá, J.C., Pereira, M.T., & Santos, G. (2022). The importance of subcontracting and its relationship with lean philosophy in automotive industry. *International Journal of Industrial Engineering and Management*, *13*(3), 186–193. DOI: 10.24867/IJIEM-2022-3-311

Silva, B., Khan, M., & Han, K. (2018). Load balancing integrated least slack time-based appliance scheduling for smart home energy management. *Sensors*, *18*(3), 685–701. DOI: 10.3390/s18030685

Tannady, H., Gunawan, E., Nurprihatin, F., & Wilujeng, F. (2019). Process improvement to reduce waste in the biggest instant noodle manufacturing company in South East Asia. *Journal of Applied Engineering Science*, *17*(2), 203–212. DOI: 10.5937/jaes17-18951

Tyagi, N., Tripathi, R.P., & Chandramouli, A.B. (2016). Single machine scheduling model with total tardiness problem. *Indian Journal of Science and Technology*, *9*(37). DOI: 10.17485/ijst/2016/v9i37/97527

Wang, W., Zhang, C., Chen, X., Li, Z., Ding, H., & Wen, X. (2018). An on-the-fly scheduling strategy for distributed stream processing platform. *2018 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Ubiquitous Computing & Communications, Big Data & Cloud Computing, Social Computing & Networking, Sustainable Computing & Communications (ISPA/IUCC/BDCloud/SocialCom/SustainCom)*, 773–780. DOI: 10.1109/BDCloud.2018.00116

Wu, G.H., Pourhejazy, P., Li, W. X., & Wu, T.H. (2024). A new dispatching mechanism for parallel-machine scheduling with different efficiencies and sequence-dependent setup times. *Decision Analytics Journal*, *10*, 1–11. DOI: 10.1016/j.dajour.2024.100432

Yang, F., Davari, M., Wei, W., Hermans, B., & Leus, R. (2022). Scheduling a single parallel-batching machine with non-identical job sizes and incompatible job families. *European Journal of Operational Research*, *303*(2), 602–615. DOI: 10.1016/j.ejor.2022.03.027

Zhao, Y., Wang, Y., Tan, Y., Zhang, J., & Yu, H. (2021). Dynamic jobshop scheduling algorithm based on deep q network. *IEEE Access*, *9*, 122995–123011. DOI: 10.1109/ACCESS.2021.3110242

Zhou, Y., Yang, J.-J., & Zheng, L.-Y. (2019). Hyper-heuristic coevolution of machine assignment and job sequencing rules for multi-objective dynamic flexible job shop scheduling. *IEEE Access*, *7*, 68–88. DOI: 10.1109/ACCESS.2018.2883802