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Design Of A Digitalization System For Machine Scheduling And Allocation In Flexible Job Shop Heavy Equipment Manufacturing Industry

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ABSTRACT
This study aims to develop a digitalized scheduling system based on the Flexible Job Shop (FJS) model to optimize production efficiency in the heavy equipment manufacturing industry. The heavy equipment manufacturing industry faces significant challenges in achieving production efficiency due to its high-mix, low-volume (HMLV) nature and the complexity of production processes. The research follows a structured approach, beginning with Focus Group Discussions (FGDs) to gather stakeholder requirements. These requirements are translated into a House of Quality (HoQ) matrix to prioritize features for the dashboard. A literature review identifies optimal scheduling methods, with a focus on FJS and heuristic scheduling rules. The dashboard is developed using JavaScript, PHP, Node.js, and PostgreSQL, and deployed on Amazon Web Services (AWS). The system undergoes black-box testing to ensure functionality and reliability before implementation. The study identifies the Earliest Due Date (EDD) method as the most effective scheduling approach, with an average delay of 3.2 days, utilization of 29%, and completion time of 14.33 days. The implementation of the digitalized scheduling system increased on-time production from 70.56% to 92.8% and improved production achievement from 92.78% to 97.4%. The dashboard application successfully integrates real-time data, adaptive scheduling, and operational features, such as a start-stop system and machine load recommendations. The findings highlight the importance of digital transformation in manufacturing, particularly in optimizing resource allocation, reducing delays, and improving production efficiency. This research contributes to the field of digitalized scheduling and real-time production management by providing a practical, data-driven solution tailored to the HMLV characteristics of heavy equipment manufacturing.
Keywords: *Digitalization, EDD, Heavy Equipment Industry, Scheduling, On-time Production*

1. Introduction

The heavy equipment manufacturing industry faces significant challenges in maximizing production efficiency to cope with dynamic and competitive global conditions. Effective scheduling is crucial for meeting customer demand. This is because efficient scheduling serves as the foundation for resource allocation, workforce planning, material procurement, and coordination of production processes. Proper scheduling can optimize production flow, minimize costs, and enhance overall efficiency. One way to streamline production is by distributing the production schedule and integrating it with the production department. In agile manufacturing, machine scheduling often follows the Flexible Job Shop (FJS) model, which requires companies to adapt to frequent and rapid scheduling changes (Jia et al., 2024). The FJS concept is highly relevant in this industry as it allows for greater flexibility in allocating production resources, including both machinery and labor. The primary goal of FJS optimization is to enhance operational efficiency and productivity within the manufacturing system by minimizing the overall job completion time (Zhang et al., 2024).

A major challenge for manufacturing companies in implementing FJS is the reliance on manual scheduling systems and the lack of detailed data for production execution. With the advancement of digitalization, the need for real-time and integrated scheduling systems has grown to ensure operational efficiency. Manufacturing systems must be able to quickly and effectively respond to various production issues to maintain operational continuity and customer satisfaction. One characteristic of heavy equipment manufacturing is its high-mix, low-volume (HMLV) nature, which demands systems that can adapt to dynamic schedules (Soleymanizadeh et al., 2023). Additionally, there are frequent requests for insert production to support dynamic customer needs (Luo, 2020). The production machines used are typically complex and carry significant risks of breakdowns (Fan et al., 2024). Production often involves multiple parallel machines with dynamic arrivals and uncertain processing times (Y. Liu et al., 2024; Wu et al., 2024).

Several studies have addressed efficiency improvements in Flexible Job Shop (FJS), but there remains a gap in implementing digitalization systems to support flexible scheduling. For instance, Bryant et al. (2022) discussed stochastic production with fixed due dates but did not offer specific solutions on how digitalization can enable more flexible production planning. Didden et al., (2024) highlighted that high-mix, low-volume manufacturing requires more adaptive systems but did not explain how digitalization can be used to adjust production schedules in real time. Parente et al. (2020) emphasized the use of metaheuristics, machine learning, and hyper-heuristics as solutions for FJS but did not demonstrate concrete implementations in the heavy equipment industry. Brandimarte & Fadda, (2024) explored challenges in Just-in-Time (JIT) scheduling but did not link it to digitalization in heavy equipment manufacturing environments. One approach that has been adopted in modern manufacturing is the Just-in-Time (JIT) scheduling concept, which focuses on completing production precisely according to market demand (Brandimarte & Fadda, 2024).

According to internal company data, the average on-time production rate from March 2022 to February 2023 was 70.56%. Although the company has not set a specific target for on-time production, this achievement is considered too low and significantly impacts overall production targets. The average actual production achievement was 92.78%, still below the target of 98%. Therefore, on-time production has become a critical Key Performance Indicator (KPI) that the company must improve. To address these challenges, this study aims to develop a digitalized scheduling system based on the Flexible Job Shop (FJS) model to optimize resources in the heavy equipment manufacturing industry. The results of this research include several key features, such as integrated and real-time data, adaptive and optimal production scheduling through heuristic scheduling rules, and the integration of heuristic scheduling with digitalized manufacturing systems. This study contributes to improving production timeliness and work flexibility by implementing a digitalized scheduling system in heavy equipment manufacturing. With the adoption of digitalized scheduling systems, it is expected that heavy equipment manufacturing companies can overcome the challenges of complex production scheduling and remain competitive in the Industry 4.0 era.

2. Literature Review

Research conducted by Mathew et al. (2023) discusses strategies and solutions for digitalization in production planning and scheduling for manufacturing companies using the Engineer-to-Order (ETO) approach. A data-driven decision-making system can significantly enhance production scheduling efficiency. Serrano-Ruiz et al. (2024) explain that job assignment and sequencing on machines can optimize manufacturing processes. Meanwhile, (Luo, 2020) states that dynamic scheduling systems can complete jobs on time, maximize high-quality output, and minimize production costs. The integration of technology and data creates a more efficient and effective production system.

The heavy equipment industry shares production characteristics with ETO, such as high-mix, low-volume (HMLV). This research serves as a reference for developing a Flexible Job Shop (FJS) digitalization system, focusing on data analysis and simulation. A Hybrid Genetic Algorithm (HGA), combining genetic algorithms and tabu search, was developed to solve the Flexible Job Shop Scheduling Problem (FJSSP), which involves sequence-dependent setup times and job waiting times (Song & Liu, 2022). This study also compares various methods to determine the optimal FJS scheduling approach.

Du et al. (2024) made significant contributions to scheduling optimization by proposing an innovative Reinforcement Learning (RL) approach to handle FJSSP, including crane transportation and setup time aspects. This method demonstrates potential for improving production efficiency and can be adapted to various industrial applications. Wu et al. (2024) developed a Deep Reinforcement Learning model for FJSSP with uncertain processing times, showing better performance in reducing makespan compared to traditional methods. Meanwhile, Y. Liu et al. (2024) investigated FJSSP by considering energy consumption and proposed a multi-objective optimization algorithm to simultaneously reduce makespan and energy usage.

According to Didden et al. (2024), the First Come, First Serve (FCFS) method prioritizes jobs based on arrival order without considering processing duration. Although simple and fair, FCFS can slow down operations because long-duration jobs tend to delay the overall process (Serpa et al., 2020). To address this issue, this research aims to develop a system that dynamically adjusts production schedules during machine downtime. The Shortest Processing Time (SPT) method prioritizes jobs with the shortest duration, effectively reducing the average job completion time (Bryant et al., 2022). On the other hand, the Earliest Due Date (EDD) method prioritizes jobs with the nearest due date. While EDD is effective in minimizing delays for urgent tasks, it can inadvertently cause delays for jobs with later due dates (Fan et al., 2024). Another approach, the Critical Ratio (CR) method, balances urgent jobs and production efficiency by calculating the ratio of the remaining time until the due date to the remaining processing time (Y. Liu et al., 2024). (Hamzadayı, 2020) utilized a CR-based algorithm to optimize scheduling and conducted simulations to compare its performance with EDD and SPT, demonstrating its effectiveness in managing complex scheduling scenarios.

Sutrisno et al. (2023) provided a comprehensive analysis of four production scheduling methods (FCFS, SPT, LPT, and EDD) in the context of huller machine scheduling. The results indicate that the choice of scheduling method should align with production goals, as no single method suits all situations. This study offers valuable insights for industries aiming to optimize production processes and improve efficiency. These methods can also be applied in Flexible Job Shop (FJS) environments to overcome the limitations of conventional approaches. Key evaluation parameters for scheduling methods include release time, flow time, processing time, tardiness, and due date (Luo, 2020). Therefore, selecting the appropriate scheduling method depends on the production context and objectives, requiring consideration of various relevant parameters.

Quality Function Deployment (QFD) is a customer-oriented approach to improving quality in New Product Development (NPD) and ensuring customer involvement throughout the product specification process (Shvetsova et al., 2021). The primary tool used in QFD is the House of Quality (HoQ), which identifies customer needs, technical requirements, and their relationships. QFD integrates customer needs into product design, reduces quality issues, and enables more structured and objective decision-making (Abu Dabous et al., 2024). QFD is particularly beneficial in the design process, especially in selecting structures that best meet customer requirements.

Based on HoQ, customer needs are translated into technical attributes, which are then detailed into component specifications, operational procedures, and production requirements related to the manufacturing process. Therefore, this research develops a scheduling system based on company needs. Production scheduling is achieved through a digital scheduling system, simplifying production processes using the best available methods. For example, Elhegazy et al. (2020) used QFD to select the optimal structural system in building construction, demonstrating that QFD helps identify customer needs and translate them into technical specifications. On the other hand, black-box testing is a testing approach that focuses on system inputs and outputs without requiring knowledge of internal code. This method is particularly useful for testing APIs, as it allows testing from the end-user perspective. Black-box testing has proven effective in detecting errors, ensuring API reliability, and integrating seamlessly into software development workflows (Felicio et al., 2023). Thus, black-box testing holds significant potential for improving the quality and reliability of RESTful Web APIs in dynamic and evolving development environments.

3. Research Methods

Figure 1 shows the research flow to carry out current problems.

Fig. 1. Research flow chart

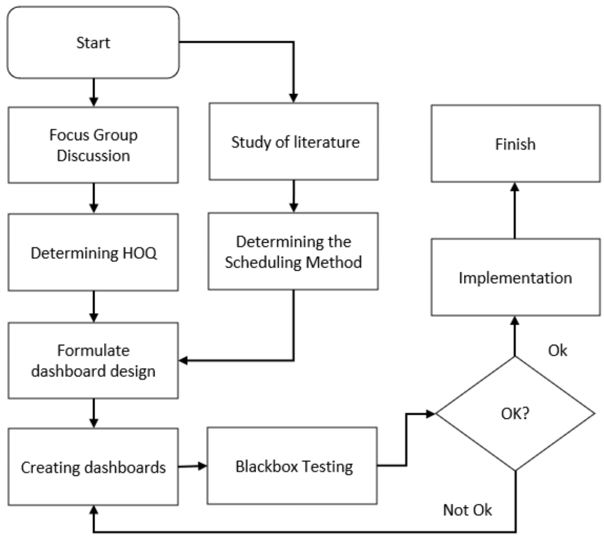


Figure 1 illustrates the step-by-step process involved in creating the dashboard application. These stages involve several stakeholders, including nesting planners, operators, and group leaders. Data is collected from various departments within the company through Focus Group Discussions (FGDs). Below is an explanation of each stage:

Step 1: Focus Group Discussion (FGD)

1. The FGD is conducted with relevant stakeholders to gather necessary data, such as the required menu features and procedures for data collection. The FGD involves participants from various departments, including:
2. Manufacturing Department: Oversees production processes. Participants include the manufacturing manager, supervisor, and foreman.
3. Production Control (PC) Department: Manages production comprehensively. Participants include the production control manager.
4. Process Engineering (PE) Department: Responsible for maintaining process standards and synchronizing master data. Participants include the PE manager and process engineering specialists.
5. Design Engineering Department: Requires features related to product drawings on the dashboard. Participants include the Engineering Technical Support Coordinator.
6. Digitalization Function: Handles all digitalization activities within the company. Participants include the digitalization function manager, programmers, and the digitalization team in manufacturing.

Step 2: Determine House of Quality (HoQ)

The results of the FGD are translated into the House of Quality (HoQ) matrix. The HoQ is designed to assist in implementation by focusing on desired characteristics. It maps out the menu requirements to be developed by programmers, enabling them to prioritize which features or functions to build first.

Step 3: Literature Studies

A literature review is conducted to explore alternative methods and systems relevant to scheduling. This step provides a reference for the research area, specifically focusing on the Flexible Job Shop (FJS) manufacturing model.

Step 4: Determine Scheduling Method

Based on the literature review, the most reliable scheduling method or system is selected. This method serves as the foundation for programming the dashboard.

Step 5: Formulate the Dashboard Design
1. Using input from the HoQ and the selected scheduling method, the dashboard design is formulated. Key considerations for the dashboard design include:
2. Integration: The dashboard must synchronize with other existing digital systems, such as the digitalized Master Production Schedule (MPS), digitalized supply chain, and digitalized product design.
3. Operational Features: The dashboard must include a start-stop system to monitor operator productivity.
4. Reporting Features: The dashboard must display reports required by all relevant stakeholders.

Step 6: Create the Dashboard
Once the dashboard design is finalized, the development process begins. This is the core and most time-consuming phase. The dashboard is reviewed periodically, with major reviews conducted at least once a month. The application is built using JavaScript for the frontend, PHP and Node.js for the backend, and PostgreSQL for the database. The system runs on a 6-core Intel i7 processor with 16 GB RAM, while the server uses Amazon Web Services (AWS) with a 4-core CPU, 16 GB RAM, and 100 GB SSD storage. Challenges during development include data integration, large data loads, data security, user experience, and system scalability. Therefore, a detailed and comprehensive development mechanism is essential.

Step 7: Black-Box Testing
After the dashboard is completed, black-box testing is conducted. Usability testing involves various stakeholders, such as nesting planners, operators, and group leaders. Testers evaluate all menu features by completing assessment forms. The goal of black-box testing is to ensure the dashboard functions as intended and to identify any bugs or issues.

Step 8: Implementation
Once black-box testing is successfully completed, the dashboard is declared Go Live. The dashboard becomes a standard tool, and its usage is formalized into the company's Standard Operating Procedures (SOP).

4. Results and Discussions
4.1. Result
The first stage of Focus Group Discussion (FGD) was conducted with several stakeholders in its interests. The FGD held on December 7, 2022, discussed the needs of each stakeholder which will be included in the dashboard. The first FGD was attended by a complete team of 11 members. The next FGD was attended by only the core members of the meeting with more detailed discussion. All FGD produced 41 inputs from every stakeholder.
Stages furthermore are pouring the desired user into the House of Quality matrix. This House of Quality can give a description related to creating a scheduling menu dashboard. The user's need was interpreted through a Focus Group Discussion (FGD) conducted previously with company stakeholders. Based on results from the FGD, several appropriate dashboard menu requirements can be collected to meet company needs can be seen in Table 1.

Table 1 – Customer Requirements

FGD results	Action	Units	Customer Requirements
Employment data want to made in a way automatically and manually so that data is more up to date for proposed assignment machine	Dashboard & Table View	Nesting Planner	Refresh Job Data
Job data that can be sorted based on range date between order and completion date, plan Work daily, filter by keywords and all data	Dashboard & Table View	Nesting Planner	Filter and Sort Suggestion machine

Appear reason Why production stop	Create	Nesting Planner	Reason Pause
Move a number allocation finished components from one PRO with excess finished quantity to another PRO with the same component PN	Updates	Nesting Planner	Move Quantity
Manage operator and PB Group Leader master data to keep it up-to-date	Create, Read, Update, Delete	Nesting Planner	User Data
Manage machine master data to keep it up-to-date	Create, Read, Update, Delete	Nesting Planner	Machine Data
Carry out future customer mapping accept PB components with PRO data	Create, Read, Update, Delete	Nesting Planner	Mapping PRO Customer Data
Carry out mapping between component with the drawing	Create, Read, Update, Delete	Nesting Planner	Mapping Image Data
Manage reason pause master data to keep it up-to-date	Create, Read, Update, Delete	Nesting Planner	Safety Factor Capacity Data
Manage customer master data to keep it up-to-date	Create, Read, Update, Delete	Nesting Planner	Customer Data
Displays the final assignment ever carried out by the nesting planner role	Dashboard & Table View	Nesting Planner	Dashboard Assign
Displays jobs that have a planned start date D+1 to D+10 from the current date	Dashboard & Table View	Nesting Planner	Job Status Dashboard
Displays a list of machines that are currently breakdown	Dashboard & Table View	Nesting Planner	
Displays existing jobs assigned and done there is a start by the operator	Dashboard & Table View	Nesting Planner	
Displays existing jobs finished done in month walk	Dashboard & Table View	Nesting Planner	
Displaying capacity machine hour each machine compared to with the existing processing time allocated to machine the based on outstanding final assignment	Dashboard & Table View	Nesting Planner	Capacity Chart
Displaying suggestion Machine Load by Engine shows distribution of suggested job assignments to every machine	Dashboard & Table View	Nesting Planner	
Carrying out filtering and sorting of job lists	Read and Download	Nesting Planner	Job Management Filters
Displays the job list that has been completed chosen previously along with a suggestion assignment machine for every work	Dashboard & Table View	Nesting Planner	Job List and Suggestion Dashboard
Carrying out final job assignments to later machine will continued to the progress operator input	Updates	Nesting Planner	Assignments
Change the previous final assignment has done. If there are existing components finished done, entered the amount to be in the machine next only the remaining required quantity is calculated	Updates	Nesting Planner	
Choose machine where the operator will work and input the actual progress of the job on the machine the	Dashboard & Table View	Operator	Election Dashboard Machine
Select the data to be displayed on the job task page	Dashboard & Table View	Operator	Outstanding & Completed Job Dashboard
Displaying information of component of every job	View	Operator	Schedule Information
Displays the drawing that has been created mapped with component	View	Operator	Component Drawing

Media input issues related to the work process something component	Create, Read, Update, Delete	Operator	Issue during Production
Media input actual progress of component job work	Create and Read	Operator	Actual Progress Input Units
Grouping a number of work and then start stop is carried out simultaneously	Create and Read	Operator	Actual Progress Input Bundle
Performs immediate start and stop from job listing page without enter to work progress detail page	Create	Operator	Actual Progress Input via Shortcut Button
Carry out actual progress input on work redo the previous one made by the Group Leader	Create	Operator	Actual Progress Input
View jobs that have been completed. Jobs are shared and become standard work, non-standard jobs, and bundling jobs. By default, it is displayed are finished jobs in 7 days final	Dashboard & Table View	Operator	All Finished Jobs Dashboard
See all bundling jobs ever created in the previous system	Dashboard & Table View	Operator	Job Bundling Dashboard
Place do related transactions with outstanding jobs	Dashboard & Table View	Group Leader	Outstanding Job
Stop a job with status started from Group Leader side (Force Stop Job)	Create	Group Leader	Outstanding Job
Change the previous machine assignment Already provided by Nesting Planner (Edit final Assignment)	Create	Group Leader	Outstanding Job
Do deactivation machine consequence breakdown and moving all jobs on the machine the going to other machines (Machine Breakdown-Apply to All Job)	Create	Group Leader	Outstanding Job
Do deactivation machine consequence breakdown and moving the desired job to a number of machine different (Machine Breakdown-Unit)	Create	Group Leader	Outstanding Job
View jobs that have been completed. Jobs are shared and become work standard, non-standard jobs, and bundling jobs. By default, it is displayed are finished jobs in 7 days final.	Dashboard & Table View	Group Leader	Finished Job
View the list of jobs that have been finished and carry out redo assignments for jobs that have been completed never finished. By default, it is displayed are finished jobs in 7 days final	Dashboard & Table View	Group Leader	Redo of Finished Jobs
Stop a job redo with status started from Group Leader side	Create	Group Leader	Redo of Finished Jobs
View the list of redo jobs	Dashboard & Table View	Group Leader	Redo Job List Dashboard

After determining customer requirements, the stages further determine customer importance Ratings. Stakeholders at the company determine Customer Importance Rating for every component Customer Requirements. As for range evaluation, there are values 1-5. The number 1 is worth very little importance, the number 2 is valuable and Unimportant, the number 3 is valuable neutral, the number 4 is valuable and essential, and the number 5 is valuable and very important. As for the results, the mark can be seen in Table 2.

Table 2 – Customer Importance Ratings

Customer Requirements	Customer Importance Rating
Refresh PB Job Data	4
Job Data Filters	3
Reason Pause	4
Move Quantity	4
User Data	3
Machine Data	3
Mapping PRO Customer Data	3
Mapping Image Data	3
Safety Factor Capacity Data	3
Customer Data	3
Dashboard Assign	5

Job Status Dashboard	5
Capacity Chart	5
Job Management Filters	5
Job List and Suggestion Dashboard	5
Assignments	5
Machine Selection Dashboard	3
Outstanding and Completed Job Data Dashboard	2
Schedule Information	2
Component Drawing	2
Issues During Production	2
Actual Progress	2
All Finished Jobs Dashboard	4
Job Bundling Dashboard	4
Outstanding Job Dashboard	4
Outstanding Job Data	3
Redo Job List Dashboard	4

Furthermore, after determining customer importance, the rating is a technical requirement. The technical requirements that answered need customers can be seen in Table 3 below.

Table 3 – Technical Requirements

Technical Requirements
Automation and manual refresh of data
Filter All Data, Field Filter, Date Filter and Plan Start Date
Reason Pause Data Up to Date
Move the Component quantity
Update operator and group leader data
Update machine data
Mapping customers who will receive components
Mapping between components and drawing
Update master data reason pause
Update customer data
View Final Assigned
Need Assign, Machine Breakdown, On Going and Finish on This Month
Actual and capacity assignment, suggestion machine load engine
filter and sort job list
show the job list
Edit and Final assignment job for machine
input actual job process machine
View job tasks
View the information of components
View drawing components
Component Process
Input Actual Progress of items and bundles, Start Stop in Homepage, Actual Progress Input Redo
View all finished jobs
View bundling jobs
View Transaction Outstanding Jobs
Force Stop, Edit Final Assignment, Machine Breakdown-Apply to All Jobs, Machine Breakdown – Unit
View Job List Redo

This is done in stages by mapping the connection between customer and technical requirements. There are 3 levels of the Determined Relationship Matrix: the ● icon is worth 9, the ○ icon is worth 3, and the ▽ icon value is 1. The results from the Relationship Matrix as shown in Figure 2.

Customer Requirements (Explicit and Implicit) / Functional Requirements	Automation and manual refresh data	Filter All Data, Field Filter, Date Filter an	Reason Pause Data Up to Date	Move the Component quantity	Update operator and group leader data	Update machine data	Mapping customer who will receive compo	Mapping between components and drawing	Update master data reason pause	Update customer data	View Final Assigned	Need Assign, Machine Breakdown, On Go	Actual and capacity assignment , suggestio	filter and sort job list	show the job list	Edit and Final assignment job for mac	input actual proress job machine	View job task	View the information of component	View drawing component	Component Process	Input Progress Actual item and bundle	View All the finished job	View bundling job	View Transaction Outstanding Job	Force Stop, Edit Final Assignment, Ma	View List Job Redo
Refresh Data Job PB	●		○	●	▽	○			▽	○						○	○				▽	○				○	
Filter Data Job		●			▽	○			▽	○				●	●			○				▽	▽		▽	○	▽
Reason Pause	○		●	▽		▽			●			○	▽			▽	▽		▽		●	○					
Move Quantity	○	○		●		○	▽	▽			▽	▽	○		○	○	○	○			○	○				▽	
User Data	▽				●		▽				▽	▽	▽														
Machine Data	○			▽		●			▽		▽	○	○	●	▽	●	●	○			○		○			○	
Mapping PRO Customer Data	○	▽	▽			●	●			●		▽	▽				▽		▽								
Mapping Image Data	○					●		●				▽	▽						▽	●							
Safety Factor Capacity Data	○		○	▽		▽	○		●			▽	○														
Customer Data	○									●	▽		▽												▽		
Dashboard Assign	○	○		○							●	○				●											
Dashboard Job Status	○	○		○		▽	○			▽	○	●	●	●	○	○	●	●			○	○	●		○	▽	
Capacity Chart	○			●		●	○					●	●		○	○	○	●				▽	●		○	▽	
Job Management Filter		▽	▽			○			▽	▽	○	●	○	●			○		▽	▽			●	▽	○		▽

Fig. 2. Relationship Matrix

The relationship matrix is obtained by calculating the customer importance rating with the mark end from the technical importance score. Ranking Technical Requirements are determined based on the multiplication between mark correlation and customer importance rating. After that, the result is added based on the group's technical requirements. Based on the results, the calculation between mark connection and customer importance rating can be seen in Table 4.

Table 4 – Technical Requirement Rankings

Technical Requirements	Ranking
Need Assign, Machine Breakdown, On Going and Finish on This Month	1
Automation and manual refresh of data	2
Update machine data	3
Actual and capacity assignment, suggestion machine load engine	3
input actual job process machine	3
View Final Assigned	4
show the job list	4
Edit and Final assignment job for machine	4
View all finished jobs	4
Move the Component quantity	5
filter and sort job list	5
View job tasks	5
Input Actual Progress of items and bundles, Start Stop in Homepage, Actual Progress Input Redo	5
View Transaction Outstanding Jobs	5
Filter All Data, Field Filter, Date Filter and Plan Start Date	6
Update master data reason pause	6
Update customer data	6
Component Process	6

Force Stop, Edit Final Assignment, Machine Breakdown-Apply to All Jobs, Machine Breakdown – Unit	6
Reason Pause Data Up to Date	7
Mapping customers who will receive components	7
View bundling jobs	7
View Job List Redo	7
Update operator and group leader data	8
Mapping between components and drawing	8
View the information of components	8
View drawing components	8

There is some research carried out as a reference to determine the method that will be carried out in the scheduling process production. Several studies are related to production scheduling, such as Serpa et al. (2020), Bryant et al. (2022), Fan et al. (2024), Y. Liu et al. (2024). The study list literature collected was determined based on similarity with conditions at company. Most of heavy equipment manufacturing companies don't have their own digital production scheduling systems. The article above has a similarity that still needs to exist in the appropriate scheduling method and still needs to own digitalization system. Besides that, the rules that heavy equipment manufacturing company's characteristics are relatively similar to those of the case study in the article above. Therefore, the article above is made as a reference in the determination process method that will be determined.

The production scheduling method is selected which will be used as the basis for programming the scheduling system in the dashboard. Production scheduling planning considers various provisions that have been determined by company stakeholders. Some of the provisions that form the basis of the scheduling model in research are as follows:

1. Raw materials needed in production are assumed to be available and ready to be used when needed
2. The loading-unloading process and transportation of sending raw materials and semi-finish between machines is not included in the start stop system and has been given an allowance time in the system
3. The operator working on each machine is assumed to be always available (no machine is off unless it is being repaired)
4. Each type of machine used only has 1 unit and can be run in parallel with other similar machines.
5. Unrelated machines can be run in parallel

Heavy equipment companies are companies that produce tools for mining, energy, construction, plantation and similar industries. This company produces heavy product tools, divided into six main categories: ground support, forestry, industrial, mining, construction oil, and gas. Most of the companies use scheduling with the method of First Come First Serve (FCFS) in the scheduling process. Thus, the request comes in more. Formerly will schedule moreover without considering time solution product or limit time settlement (due date). Consequences: This can cause lateness in the solution for several products because they must wait until the next turn and the production approach due date.

Determination-timetable production will be done by simulating production data into the scheduling method will be applied. Some methods used in the simulation are First Come, First Serve (FCFS), Earliest Due Date (EDD), Shortest Processing Time (SPT) and Critical Ratio (CR). I am writing customized data samples with a request from a party company that is disguised. Sample data to be done testing can be seen in Table 5.

Table 5 – Sample of Data Processing

Job	Enter	Deadline	Range Deadline	Order	Qty	Production-time (minutes)	Total Processing Time	Processing Time (days)
Job 1	12/12/2022	12/22/2022	10	M2-M1-M4	50	34	1700	4

Job 2	12/11/2022	12/25/2022	14	M3-M2-M1	43	71	3053	6
Job 3	12/10/2022	12/19/2022	9	M5-M3-M1	30	74	2220	5
Job 4	12/9/2022	12/20/2022	11	M1-M2-M3	25	71	1775	4
Job 5	12/13/2022	12/25/2022	12	M1-M4-M2	20	34	680	1
Job 6	12/8/2022	12/24/2022	16	M3-M1-M5	34	74	2516	5

A. First Come First Serve (FCFS)

FCFS method prioritizes work that comes more Formerly For processed more formerly. Based on the provision, the sorting work is done based on the date the work was entered. Order based on FCFS are job 6 – job 4 – job 3 – job 2 – job 1 – job 5. The results from FCFS processing can be seen in Table 6. With the use of FCFS rules, yield size effectiveness is as follows: Average completion-time is 16.17 days, utilization is achieved at 26 % Of average jobs in the system is 3.90 jobs, and delay average job is 6.3 days.

Table 6 – FCFS Data Processing Results

Job	Enter	Finished	Order	Qty	Production -time / min	Processing Time (Days)	Time-line (Days)	Limit Range Time	Delay (Days)
Job 6	12/8/2022	12/24/2022	M3-M1-M5	34	74	5	5	16	0
Job 4	12/9/2022	12/20/2022	M1-M2-M3	25	71	4	9	11	0
Job 3	12/10/2022	12/19/2022	M5-M3-M1	30	74	5	14	9	5
Job 2	12/11/2022	12/25/2022	M3-M2-M1	43	71	6	20	14	6
Job 1	12/12/2022	12/22/2022	M2-M1-M4	50	34	4	24	10	14
Job 5	12/13/2022	12/25/2022	M1-M4-M2	20	34	1	25	12	13
Total						25	97		38

B. Earliest Due Date (EDD)

EDD method prioritizes work based on range limit and fastest due date. Based on the provision, the sorting work is done based on the range limit of time worked. Order based on EDD is job 3 – job 1 – job 4 – job 5 – job 2 – job 6. The results from EDD processing can be seen in Table 7. With EDD rules, yield size effectiveness is as follows: Average completion-time is 14.33 days, utilization is achieved at 29%, Of average jobs in the system is 3.46 jobs, and delay average job is 3.2 days.

Table 7 – EDD Processing Data Results

Job	Enter	Finished	Order	Qty	Production -time / min	Processing Time (Days)	Time-line (Days)	Limit Range Time	Delay (Days)
Job 3	12/10/2022	12/19/2022	M5-M3-M1	30	74	5	5	9	0
Job 1	12/12/2022	12/22/2022	M2-M1-M4	50	34	4	9	10	0
Job 4	12/9/2022	12/20/2022	M1-M2-M3	25	71	4	13	11	2

Job 5	12/13/2022	12/25/2022	M1-M4-M2	20	34	1	14	12	2
Job 2	12/11/2022	12/25/2022	M3-M2-M1	43	71	6	20	14	6
Job 6	12/8/2022	12/24/2022	M3-M1-M5	34	74	5	25	16	9
Total						25	86		19

C. Shortest Processing Time (SPT)

SPT is a prioritizing method of completion of the production process based on the shortest processing time. Based on the provision, the sorting work is done based on-time processing. Order based on SPT are job 5 – job 1 – job 4 – job 3 – job 6 – job 2. The results from SPT processing can be seen in Table 8. With SPT rules, yield size effectiveness is as follows: Average completion-time is 11.94 days, utilization is achieved at 35%, Of average jobs in the system is 2.88 jobs, and delay average job is 3.2 days.

Table 8 – SPT Processing Data Results

Job	Enter	Finished	Order	Qty	Production-time / min	Processing Time (Day)	Time-line (Days)	Limit Range Time	Delay (Day)
Job 5	12/13/2022	12/25/2022	M1-M4-M2	20	34	1	1	12	0
Job 1	12/12/2022	12/22/2022	M2-M1-M4	50	34	4	5	10	0
Job 4	12/9/2022	12/20/2022	M1-M2-M3	25	71	4	9	11	0
Job 3	12/10/2022	12/19/2022	M5-M3-M1	30	74	5	13	9	5
Job 6	12/8/2022	12/24/2022	M3-M1-M5	34	74	5	19	16	3
Job 2	12/11/2022	12/25/2022	M3-M2-M1	43	71	6	25	14	11
Total						25	72		19

D. Critical Ratio (CR)

CR method prioritizes work with count time remainder until with limit time the workmanship. Based on the provision, the sorting work is done based on the smallest CR. Order based on CR is job 3 – job 2 – job 1 – job 4 – job 6 – job 5. The results from CR processing can be seen in Table 9. With CR rules, yield size effectiveness is as follows: Average completion-time is 11.94 days, utilization is achieved at 35%, of average jobs in the system is 2.88 jobs, and delay average job is 3.2 days.

Table 9 – CR Processing Data Results

Job	Enter	Finished	Order	Qty	Production-time / min	Processing Time (Day)	Time-line (Days)	Limit Range Time	Delay (Day)	CR
Job 3	12/10/2022	12/19/2022	M5-M3-M1	30	74	5	5	9	0	1.95
Job 2	12/11/2022	12/25/2022	M3-M2-M1	43	71	6	11	14	0	2.20
Job 1	12/12/2022	12/22/2022	M2-M1-M4	50	34	4	15	10	5	2.82
Job 4	12/9/2022	12/20/2022	M1-M2-M3	25	71	4	18	11	8	2.97
Job 6	12/8/2022	12/24/2022	M3-M1-M5	34	74	5	23	16	8	3.05
Job 5	12/13/2022	12/25/2022	M1-M4-M2	20	34	1	25	12	13	8.47

Total	25	97	34

After each data processing is processed, the following chosen scheduling method is relatively effective. An effective schedule is determined based on the indicator's evaluation schedule that the party company has given a weight percentage. Weight indicator evaluation as listed in Table 10, and a recap of results from every method as listed in Table 11.

Table 10 – Percentage of Evaluation Indicators

Criteria	Percentage
Completion-time	10%
Utilization	20%
Average Number Work	30%
Average Delay	40%
Amount	100%

Table 11 – Summary and Results of Percentage Calculation

Indicator		Completion Time (days)	Utilization (%)	Average Number Work / day (job)	Average Delay (days)	Total
Recap	FCFS	16.17	26%	3.90	6.3	
	EDD	14.33	29%	3.46	3.2	
	SPT	11.94	35%	2.88	3.2	
	CR	16.09	26%	3.88	5.7	
Points	FCFS	5	20	20	5	50
	EDD	15	10	10	20	55
	SPT	20	5	5	20	50
	CR	10	20	15	10	55
Percentage	FCFS	0.5	4	6	2	12.5
	EDD	1.5	2	3	8	14.5
	SPT	2	1	1.5	8	12.5
	CR	1	4	4.5	4	13.5

After recapping, each parameter is assessed by the method of ranking and awarded marks for rank 1 is given 20 marks, rank 2 is given 15 marks, rank 3 is given 10 marks, and a rank of 4 is given a value of 5, after that, value have been calculated based on percentage by indicators that have been determined. Based on the weight percentage results calculation, the method with the highest mark is the Earliest Due Date (EDD). This is in accordance with what was stated by Khalida & Giovanny (2023) who stated that the EDD method is effective to minimize tardiness in parallel machines. Apart from that, research conducted by Roychowdhury et al. (2017) explains that scheduling the earliest due date (EDD) is optimal for parts that are not late in the context of many problem formulations.

The furthermore stages are designing a scheduling dashboard design system. Three users will be involved in production scheduling system. The users are nesting planner, operator, and group leader. Features that all three menus can access can be seen according to Figures 2, 3, and 4.

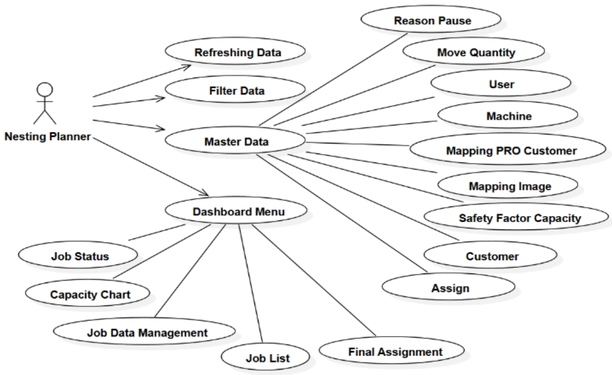


Fig. 3. Use Case Diagram Nesting Planner

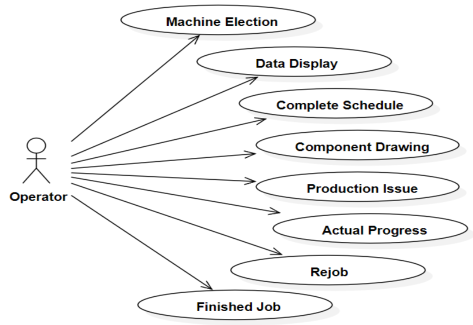


Fig. 4. Use Case Operator Diagram

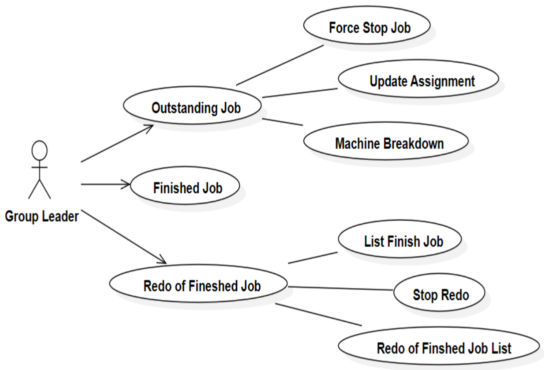


Fig. 5. Use Case Group Leader Diagram

Based on the use case diagram in Figure 3-5, the user nesting planner has a data refreshing menu, data filter, master data, and nesting planner dashboard. Operator users have a menu viz machine election, data display, complete schedule, component drawing, production issue, actual progress, job, and finished job. As for users, the group leader has a menu i.e., outstanding jobs, finished jobs, and redo of finished jobs. After creating a use case diagram for each menu, a mockup system dashboard image scheduling production was made as shown in Figure 6-9.

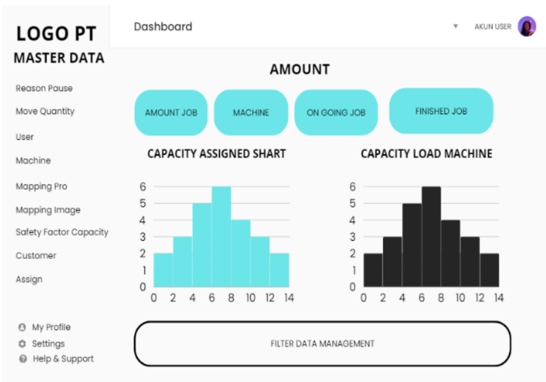


Fig. 6. Dashboard Mockups

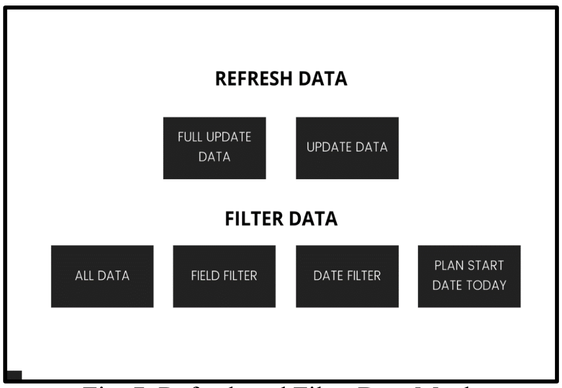


Fig. 7. Refresh and Filter Data Mockups

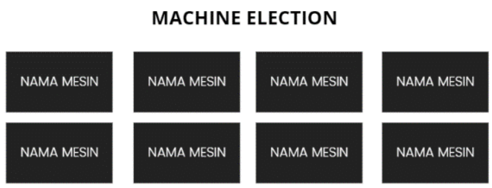


Fig. 8. Election Machine Mockups

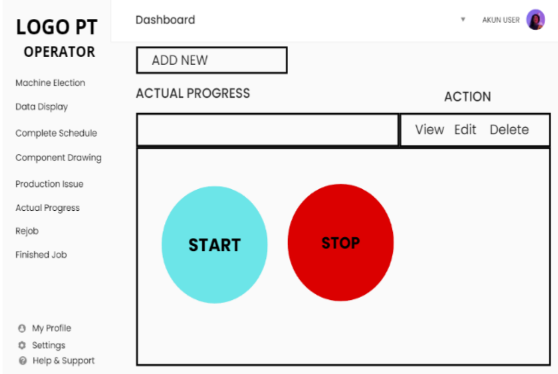


Fig. 9. Actual Progress Mockups

The dashboard of production scheduling is made using PHP and used website-based system. The dashboard is named PB Engine. PB Engine provides data for users to monitor the production capacity of each machine and provides suggestion system for nesting planner to select the appropriate machine to be used by considering machine loading capacity and capabilities. There are three modules of the main system application, namely:

1. Master data module: Module that includes management of primary data systems required in production
2. Planner Module: This module contains a mechanism for suggesting machines to be used as well as work orders for those machines
3. Operational module: Module that contains data on the work that must be done on each machine and the start-stop system that will be carried out by the operator.

The three modules are displayed in one web-based application that can accessed via a browser (recommended using Chrome). The display from some menus as shown in Figure 10-13.

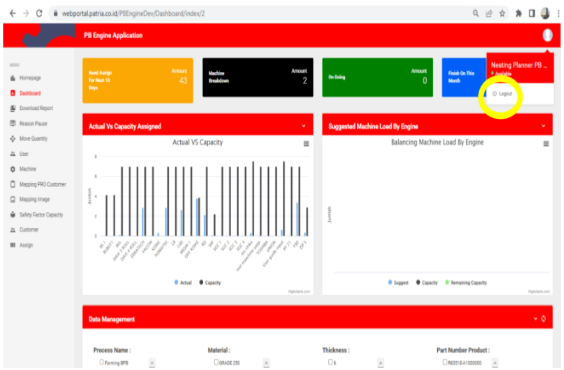


Fig. 10. Dashboard Data

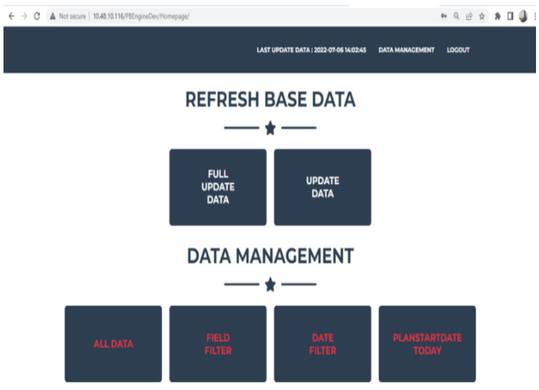


Fig. 11. Dashboard Data Management

Fig. 12. Machine Election

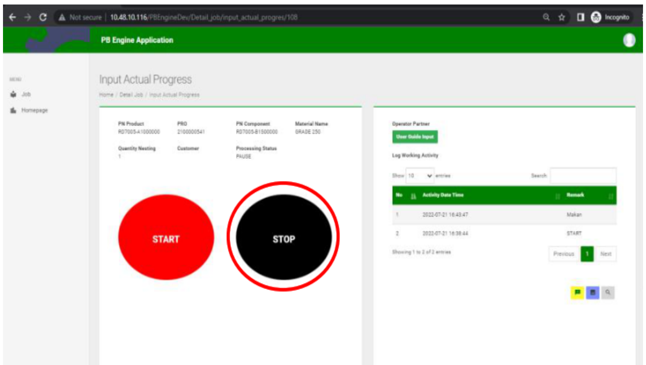


Fig. 13. Actual Progress

This stage is tested stage for the application by using the black box method. Application will be tested by using several scenarios that testers have made. The scenario is considered successful if the testing results are already the expected results. Through black-box testing, we can find out the level of success of each function and the success of the application in general. Example of test results from three respondent can be seen as follows:

Table 12 – Assign and Update Data of Blackbox Testing

Roles	Scenarios	Test Cases	Expected Results	Actual Results	Decision
Nesting Planner	Enter the Assign menu	Click the "Assign" menu	Enter the Assign menu	Enter the Assign menu	OK
Nesting Planner	Arrange amount of data displayed in One page	Choose number of other entries for is displayed	The amount of data displayed in One page changed in accordance choice	The amount of data displayed in One page changed in accordance choice	OK
Nesting Planner	Looking for assignments	Type the assignment you want searching for	List filtered according to the assignment typed	List filtered according to the assignment typed	OK
Nesting Planner	Arrange order of customer list	Click the column header you want sorted	The assignment list appears in accordance selected order	The assignment list appears in accordance selected order	OK
Nesting Planner	Interesting all data for enter to the PB Engine scheduler	Click "Full Update Data" button	All data is withdrawn enter to PB Engine	All data is withdrawn enter to PB Engine	OK
Nesting Planner	Interesting all data for enter to the PB Engine scheduler	Click "Full Update Data" button	Incoming data calculated repeat for the latest suggestions	Incoming data calculated repeat for the latest suggestions	OK
Nesting Planner	Attract new data to enter to the PB Engine scheduler	Click "Update Data" button	New data withdrawn enter to PB Engine	New data withdrawn enter to PB Engine	OK
Nesting Planner	Attract new data to enter to the PB Engine scheduler	Click "Update Data" button	New data calculated repeat together with previous data for the latest suggestions	New data calculated repeat together with previous data for the latest suggestions	OK

Based on the test results, the system is in accordance with the company's provisions and needs. The production scheduling system can now be used for operations. It is hoped that in the future there will be further system development to make it even better.

4.2. Discussion

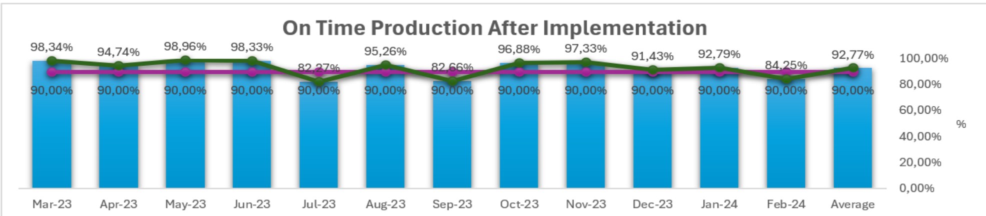
The implementation of this system was monitored and evaluated over a period of one year. The primary focus was to assess the impact of the system on achieving on-time production. The results demonstrate that the Flexible Job Shop (FJS)-based dashboard application, integrated across various units, significantly enhances production efficiency in the heavy equipment manufacturing industry. Additionally, this research adopts the FJS concept to address the challenges of high flexibility in resource allocation. This aligns with studies by Y. Wang & Zhu, (2021) and (Azzouz et al., 2017), which emphasize the importance of flexibility in production scheduling.

The dashboard application is designed with a user-friendly and adaptive interface, emphasizing functionality that enhances flexibility and adaptability. This is consistent with findings from Schiller et al. (2024) and Mende et al. (2023). Furthermore, the application enables the scheduling system to become integrated, dynamic, and real-time. This aligns with research by Chang et al. (2022), which utilizes Reinforcement Learning (RL) for dynamic scheduling. However, this study focuses specifically on heavy equipment manufacturing with high-mix, low-volume (HMLV) characteristics, distinguishing it from more general studies. This focus is supported by Didden et al. (2023)

The study identifies critical operations that impact production efficiency in the heavy equipment industry, consistent with findings by Bordignon et al. (2022). The scheduling approach adopts lean manufacturing principles to optimize production flow, as reinforced by Dewadi et al. (2024). These principles help reduce waste and improve production efficiency. The research also leverages digital technology to enhance production visibility and efficiency, aligning with studies by L. Wang et al. (2022) and (Tomaschko et al., 2024). The dashboard application includes malware detection features and undergoes black-box testing to ensure system security and reliability. This is essential, as highlighted by Schmitt (2023), Garousi et al. (2020) and Alarie et al. (2021).

The study compares several scheduling methods, including First Come First Serve (FCFS), Earliest Due Date (EDD), Shortest Processing Time (SPT), and Critical Ratio (CR). The results indicate that the EDD method is the most effective. This finding aligns with research by Bari & Karande (2022), Khalida & Giovanny (2023) and Roychowdhury et al. (2017), which demonstrate the effectiveness of EDD in reducing delays. However, this study has not fully implemented digitalization within the EDD method. Additionally, EDD minimizes completion time, as supported by Zanjani et al. (2021).

With a digitalized system, work processes become significantly more efficient compared to manual systems. This is reinforced by Abedinnia et al. (2017), who emphasize the need for automated systems to enhance work effectiveness. Based on Figure 14, the dashboard application successfully increased on-time production from 70.56% to 92.8% and improved production achievement from 92.78% to 97.4%. These results demonstrate optimal resource allocation, reduced waiting times, and improved machine utilization. These findings are supported by X. Liu et al. (2025), who highlight the importance of optimization in scheduling.



	Mar-23	Apr-23	May-23	Jun-23	Jul-23	Aug-23	Sep-23	Oct-23	Nov-23	Dec-23	Jan-24	Feb-24	**Average**
On-time Production	98,34%	94,74%	98,96%	98,33%	82,27%	95,26%	82,66%	96,88%	97,33%	91,43%	92,79%	84,25%	**92,77%**
Target On Time	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	90,00%	**90,00%**
Production Achievement	99,45%	99,12%	99,48%	98,33%	93,64%	96,12%	94,22%	98,44%	98,67%	98,57%	97,30%	95,28%	**97,39%**

Fig. 14. On-time Production After Implementation

The dashboard application can respond to schedule changes in real-time, contributing to smart manufacturing scheduling, as described by Serrano-Ruiz et al. (2021). This study also aligns with findings by Mathew et al. (2023), which state that data-driven systems can enhance production scheduling efficiency. Moreover, the digitalized system enables companies to remain competitive in the Industry 4.0 era, as explained by Abdallah et al. (2021)

This research makes significant contributions to the fields of digitalized scheduling and real-time scheduling, areas that have not been extensively explored in previous studies. Additionally, the study underscores the importance of transitioning from manual to digital systems to improve production performance. This aligns with research by Schumacher et al. (2020) which emphasizes the critical role of digital transformation in enhancing efficiency and productivity.

5. Conclusion

The Earliest Due Date (EDD) method has been identified as the most effective production scheduling method based on four evaluation indicators: average delay (3.2 days), average number of jobs (3.46 jobs), utilization (29%), and completion time (14.33 days). These indicators were weighted as follows: completion time (10%), utilization (20%), average number of jobs (30%), and average delay (40%). Based on the House of Quality (HoQ) analysis, the company requires a main menu for the operational dashboard, including features such as a job list menu with specified features, monitoring for machine damage, work in progress, and completion, an automation and manual data refresh menu and a machine update data menu. Additionally, the available menus support tactical dashboards, including capacity menus featuring capacity assignments, recommended machine load machines and actual process work machine input menus (start-stop system).

The implementation of digital scheduling has significantly improved the company's KPIs. On-time production increased to an average of 92.8% (from March 2023 to February 2024), up from the previous average of 70.56% (from March 2022 to February 2023). This improvement also led to an increase in production achievement, rising from 92.78% to 97.4%. The findings from this analysis are expected to be highly beneficial for heavy equipment manufacturing companies. However, there is still room for improvement in both scheduling methods and dashboard menu requirements.

For future research, the following suggestions are proposed conduct a comparative analysis with other production scheduling methods to further enhance effectiveness and productivity, update the technology used in developing website-based scheduling systems, develop dashboards utilizing AI and machine learning for better flexibility and adaptability and perform further analysis to determine more comprehensive indicators for assessing production scheduling methods.

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