The Optimization Inventory Process on Identical Machine Job Shop with Multiple Setups Using Genetic Algorithm

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In every production process, whether in a flow shop or a job shop, inventory is inevitable. However, for some people or companies, its presence is often not a significant concern. On the production floor, inventory is categorized into two types: product inventory and work-in-process inventory. Inventory arises when production scheduling incorporates lot size into production planning. In flow shop scheduling, inventory typically accumulates at the beginning and end of the process (finished goods). In contrast, in job shop scheduling, inventory not only appears at the start and end of each process but also during the middle of the machine process. This occurs if a machine requires more than one setup to complete a product. Currently, there is no research that addresses the impact of inventory on job shop scheduling where each machine necessitates multiple setups while ensuring the completion time does not exceed the due date and production capacity. Given that job shop scheduling with multiple machines, products, and setups is an NP-hard problem, this study will employ a genetic algorithm for the optimization process. The results of inventory optimization using a genetic algorithm show that production costs were reduced from $48,519 to $43,140, representing an 11% decrease.

Keywords: Dispatching, Genetic Algorithm, Inventory process, Multiple setups, Optimization.

1. Introduction

The job shop scheduling problem involves coordinating tasks across multiple machines. Each task consists of a sequence of operations to be completed without interruption on specific machines. The objective is to find a processing order for each machine that minimizes the makespan, representing the completion time of the last operation. This problem is studied as a stochastic model, examining the role of manufacturing process flexibility in single-period, single-stage production settings. Here, different products are produced across limited-capacity facilities [1]. Jobs arrive sequentially to a single available machine. Each job is executed individually, with variations in process time, setup time, weight, and due date. Another significant scheduling challenge involves distinguishing between setup time and processing time for jobs. This is particularly crucial when setup time constitutes a substantial portion of the overall processing duration. By treating setup times separately, jobs can potentially be completed more efficiently since setup for the next job can occur during machine idle periods. However, when setup times are integrated into processing times, this optimization opportunity is lost [2][3][4]. However, it's frequently overlooked, particularly for products with significant dimensions, necessitating multiple setup times. This can impact the level of in-process inventory that accumulates, if such discussions exist, they primarily focus on in-process inventory within the assembly process, typically following a flow shop sequence. However, there's a notable absence of discourse concerning inventory processes in machine operations employing a job shop approach (with numerous product types and variations) and also featuring multiple setups.

This research explores the in-process inventory arising from the initial scheduling conducted by the company, employing the First Come First Serve (FCFS) dispatching method. Subsequently, the optimization the inventory process while ensuring adherence to customer-defined completion times. The optimization method employed utilizes a genetic algorithm approach. The article concludes with a discussion of the optimal number of inventory processes in relation to the initial conditions, as well as a strategy for optimizing the inventory process in the context of job shop scheduling for identical machines with multiple configurations.

2. LITERATURE REVIEW

2.1 Lot Sizing and Scheduling

Efficient production control is essential in manufacturing as it ensures a steady and economical production process, leading to enhanced operational efficiency. In a job shop layout, similar process equipment or work systems are grouped within enclosed units, allowing for various product types to follow different routes. A job shop is considered flexible when processes can be executed by multiple tools simultaneously, enabling identical tools to work in parallel. A flexible workshop is classified as a complex job shop under the conditions outlined by [5]: 1). Re-entrant flow of jobs (e.g., a job requiring multiple operations on the same machine); 2). Sequence-dependent setup times; 3). Time-related dependencies between processes; 4). Frequent machine failures and interruptions; 5). Variations in processing times for jobs on the same equipment; 6). Imposed deadline dates for tasks; 7). Diverse process types, such as batch processing versus single job processing; 8). Varying batch sizes and; 9). Utilization of different tools in operations.

There has been limited research on stochastic scheduling problems, where certain job characteristics are represented as random variables, and machines may experience random breakdowns, with separate setup times playing a role [3][6]. Various solution approaches, including mathematical programming methods, artificial intelligence techniques, local search algorithms, and metaheuristic approaches, have been proposed to tackle the complexity of Flexible Job Shop Problems (FJSP) [7].

The complexity of the Lot Size and Scheduling Problem (LSP) is determined by the factors under analysis, shaping the formulation of mathematical models and the evolution of computational methods for problem-solving. Figure 1 illustrates the foundational characteristics of LSPs [8][9]

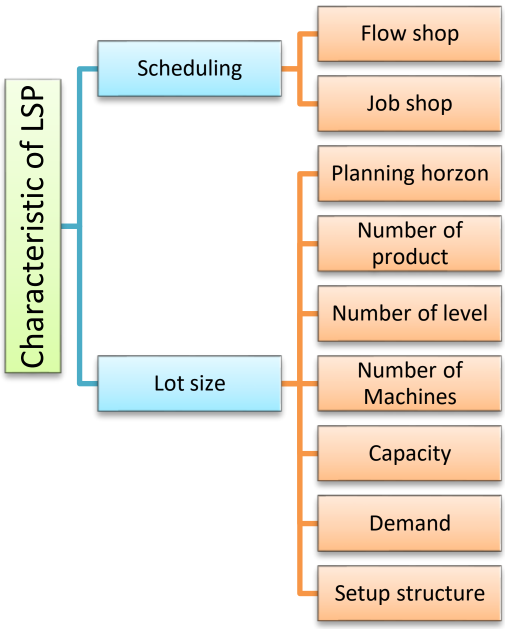


Figure 1: Characteristic of LSP

In LSP problems, job shop scheduling presents a significant challenge, as determining the lot sizes is influenced by demand while still needing to account for the number of products, available capacity, and the setup time required for each product in the machine processes.

2.2 Dispatching

In practical scenarios, dispatching rules are often employed to assist with larger problem sizes. Although they may not offer the same level of optimization as local search approaches, they are frequently favored due to their ease of implementation and minimal complexity. When a machine becomes available, a prioritized dispatching rule evaluates the pending jobs and selects the one with the highest priority for execution next. Some recent studies in classical JSP have explored the concept of Dispatching Rule Combination (DRC), which involves heuristic combinations of single dispatching rules aimed at capitalizing on their individual strengths. Empirical evidence suggests that combined dispatching rules can outperform single dispatching rules when the schedule quality is carefully integrated [10].

The dynamic field of simultaneous lot sizing and scheduling is fueled by diverse industrial applications. These applications often entail single- or multiple-stage production systems with one or more parallel, predominantly heterogeneous machines (production plants) per stage. Notably, sequence-dependent changeover delays are prevalent. Industries like food and beverage, which typically produce items in bulk for inventory, exemplify such applications. Given the substantial effort involved in changeovers, the selection of appropriately sized lots is crucial, alongside meticulous determination of their sequencing. The intricate interplay between these decision types underscores the need for an integrated planning approach [11].

Usually, a hierarchy of dispatching rules is employed, with certain rules taking precedence over others depending on the circumstances. For instance, if two processes need to be synchronized for optimal execution, this synchronization takes precedence over other dispatching strategies aimed at meeting due dates. However, attempts to use a single set of dispatching rules for all tools, as discussed in [5] and [12][13], have not been successful.

2.3 Inventory

The inventory not only complicates on-site material management, but it also blocks the movement of corporate cash. As a result, it is critical to fine-tune inventory levels in addition to improving production efficiency. However, it's vital to understand that inventory levels are irregular metrics [14]. In current manufacturing activity, especially for intricate and sizable products require process on heavy machine tools, the components are usually substantial and weighty, necessitating prolonged machining operations during processing. Moreover, during the assembly phase, these components frequently involve extended assembly durations, attributed to factors such as setup time, tooling preparation and time operation for assembly and time for delivery date. [15].

Historically, in order to enhance efficiency in production, the formulation of the part processing plan and assembly sequence plan involved the execution of job shop sequencing and assembly sequence procedures independently. Figure 2 depicts the standard production procedure for a product comprising n components [15].

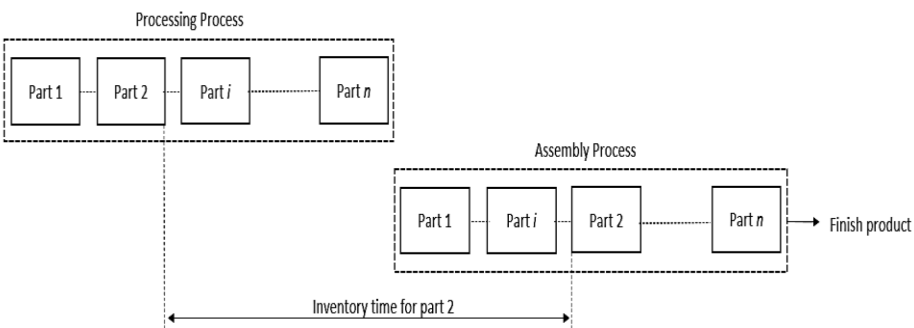


Figure 2: Traditional production process

This method allows for the minimization of makespan in part processing through job shop sequencing, while reducing time of assembly process or cost can be achieved through assembly sequence processing. However, it often leads to extended inventory durations for the parts before their assembly into the final product, as illustrated in Part 2. As a result of the sequential nature of this manufacturing process, total production completion times are frequently extended. In order to mitigate this concern, one could set up a simultaneous production process—illustrated in Figure 3—in which part processing and assembly take place concurrently. With this concurrent approach, assembly of a part can start immediately after its processing is completed.

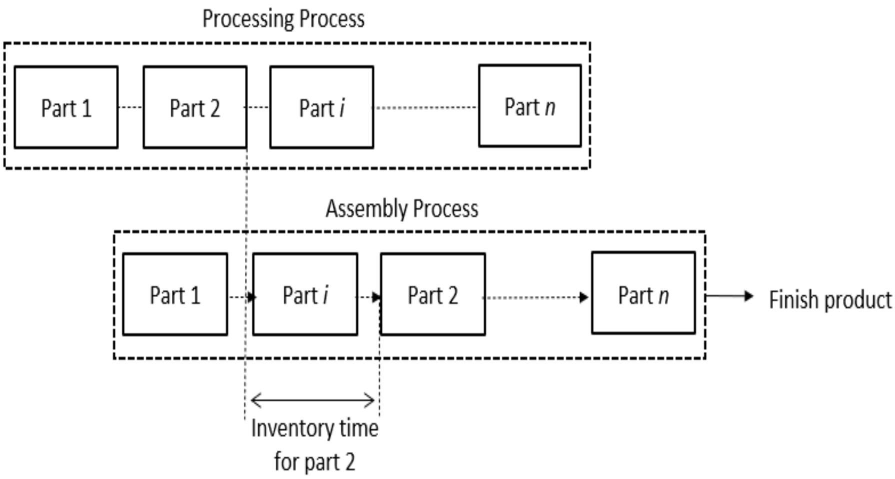


Figure 3: Initial Concurrent processing

As shown in Figure 3, there's inventory time for Part 2 because of its early completion in the part processing stage. In addition, because the processing of Part i has not yet been completed, assembly of Part i cannot commence at the designated time in the assembly sequence plan. This causes a delay for Part i throughout the assembly procedure. Figure 4 illustrates an amended concurrent production process schedule that accounts for the assembly waiting time of Part i. As a consequence, the overall production completion time for the product is extended.

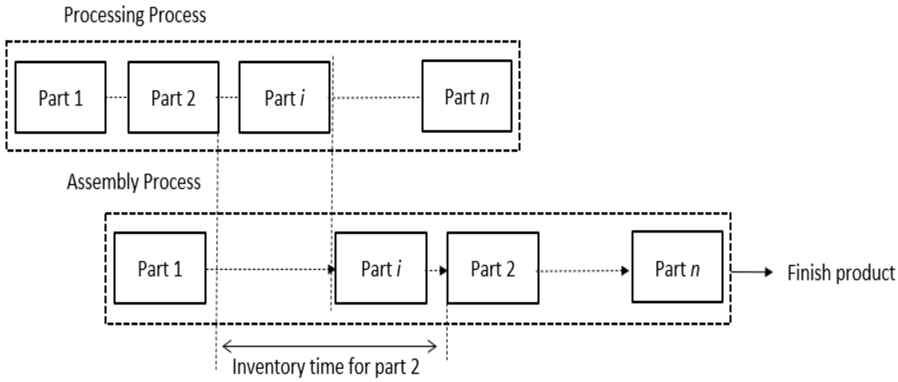


Figure 4: Modified concurrent process

Nevertheless, this modification will lead to the accumulation of inventory time for Part i. As a result, the total production completion time of the product has been modified in conjunction with the execution of this modified concurrent production process plan.

2.4 Genetic Algorithm

Genetic Algorithms (GA) have been applied to various combinatorial optimization problems, particularly in assignment and scheduling tasks. Since their development in the 2000s, GA has been utilized for optimization purposes in production, manufacturing, and operations management [16]. However, genetic algorithms were perceived as relatively costly compared to dispatching methods [13].

[17] to address parallel machine scheduling issues involving preparation times that are dependent on sequences, genetic algorithms were implemented. A hybrid genetic algorithm approach was implemented, wherein the genetic algorithm is utilized to allocate tasks to parallel machines, while dispatching rules are employed to resolve sub-problems on individual machines. Similarly, [13] employed heuristics incorporating genetic algorithms to solve the Pm | batch, incompatible | ∑ wj Tj problem. Job-to-machine assignments are facilitated through the utilization of a genetic algorithm (GA). The application of the GA in this study encompasses several stages: code generation, initialization, crossover, selection, evaluation, mutation, crossover, and termination criteria.

3. METHODOLOGY

A theoretical structural model is a model that represents the assigning jobs into the machines. The genetic algorithm evaluates each assignment subsequent to the assignment phase by summing the aggregated weighted tardiness values of the individual machine sequences. These values are acquired on each machine via the implementation of dispatching and scheduling rules. The aggregation occurs across all machines. As illustrated in Figures 5, the genetic algorithm converges to assignments that generate favourable solutions with respect to total weighted tardiness.

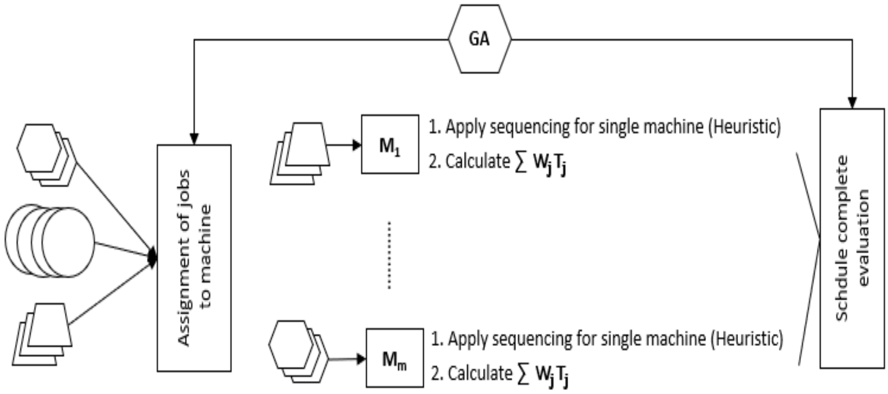


Figure 5: Jobs assign to machine

During each search iteration, the considerations include the inventory costs incurred during the process and ensuring that the completion time does not surpass the desired due date specified by the customer.

4. RESULTS

4.1 Model Development

This study conducted job shop scheduling for identical parallel machines, where each machine necessitates multiple setup times for each product run. Therefore, the process inventory computed in this research represents the inventory accumulated on a machine due to product batches and multiple setups. A comprehensive depiction of process inventory is provided in Figure 6 for M1/ J1/L4/S2.

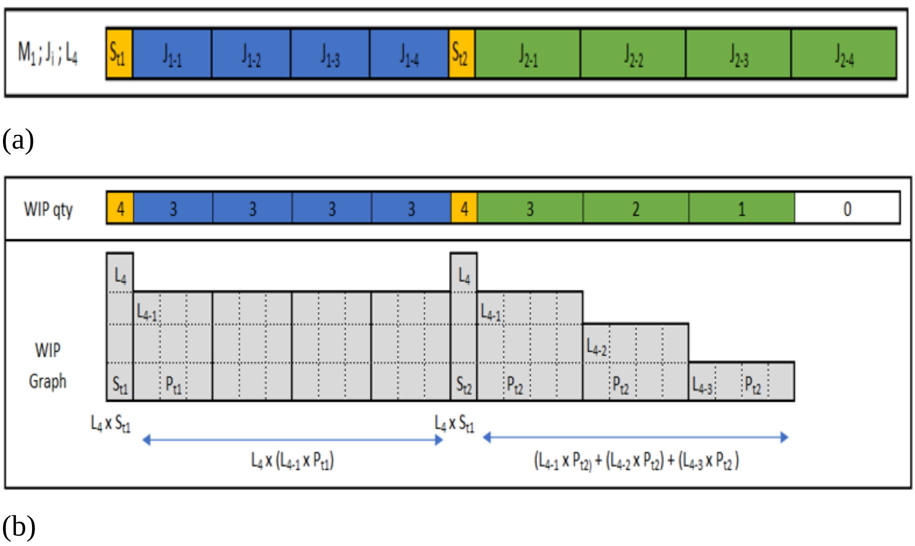


Figure 6: Illustration inventory process M1/J1/L4/S2

Based on the above illustration, the inventory process model development can be expressed by the following equation:

First Process:

$$\mathbf{WIP_1 = (L_4 x S_{t1}) + L_4\, x\, (L_3 x P_{t1})} \quad (1)$$

$$\mathbf{WIP_1 = (L_L x S_{t1}) + L_L\, x\, (L_{L-1} x P_{t1})} \quad (2)$$

Second Process:

$$\mathbf{WIP_2 = (L_4\, x\, S_{t2}) + (L_3\, x\, P_{t2}) + (L_2\, x\, P_{t2}) + (L_1 x\, P_{t2})} \quad (3)$$

$$\mathbf{WIP_2 = (L_L x\, S_{t2}) + (P_{t2}) \sum_{k=1}^{L-1} (L_{L-1})} \quad (4)$$

Hence, the total inventory process for multiple setups in job shop machine scheduling equals the sum of inventory process 1 and inventory process 2. This can be represented in formulaic notation as follows:

$$\mathbf{WIP = (L_L x S_{t1}) + L_L\, x\, (L_{L-1} x P_{t1}) + (L_L x\, S_{t2}) + (P_{t2}) \sum_{k=1}^{L-1} (L_{L-1})} \quad (5)$$

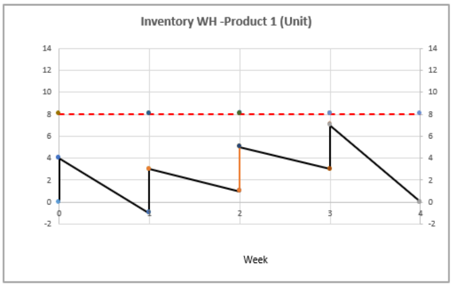
4.2 Initial Scheduling Identical Machine Job shop on Multiple Setups

For the initial scheduling sequence, the First-Come, First-Served (FCFS) approach is assumed, and the standard practice in the production department is to determine the lot size by dividing the total monthly demand into weekly demands. Table 1 display the one-month initial loading based on common practice:

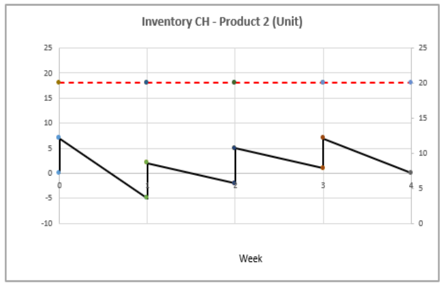
Table 1: Initial loading and requirement

Product	Week 1		Week 2		Week 3		Week 4	
	Load	Req	Load	Req	Load	Req	Load	Req
1	4	6/16	4	7/16	4	9/16	4	16/16
2	7	12/27	7	16/27	7	20/27	6	27/27
3	7	10/27	7	14/27	7	18/27	6	27/27
4	3	3/12	3	6/12	3	7/12	3	12/12

The inventory overview presented on Figure 7 below reflects the outcome of the aforementioned planning for the four products. The red line depicted on the graph indicates the maximum quantity of products that can be stacked on a pallet.



(a)



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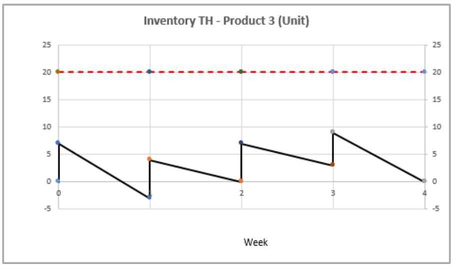

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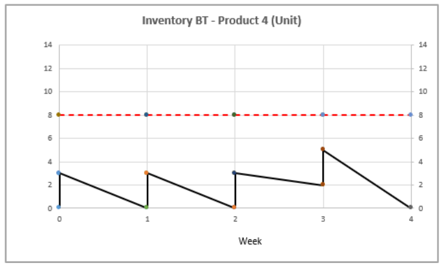


(d)

Figure 7: Initial inventory, a). Product 1; b). Product 2; c). Product 3 and; d). Product 4

The initial scheduling can be seen as Table 2 below:

Table 2: Initial schedule and cost

Item	Job sequence				Cost of setup and
	Wk1	Wk2	Wk3	Wk4	initial invt. ($)
1	P1(4)	P1(4)	P1(4)	P1(4)	802
2	P2(7)	P2(7)	P2(7)	P2(6)	493
3	P3(7)	P3(7)	P3(7)	P3(6)	307
4	P4(3)	P4(3)	P4(3)	P4(3)	1,235
					2,836
Cost. Inv. ($)	14,015	4,695	1,450	18,420	38,580
Inv. Space ($)					4,000
Cap. Sched ($)					763
Late del. ($)					2,340
Total ($)					48,519

4.3 Optimization Scheduling Identical Machine Job shop on Multiple Setups

In the genetic algorithm process, the chromosomes used in this research encompass demand, lot size, dispatching, setup time, and processing time. The arrangement of these chromosomes is illustrated in Figure 8.

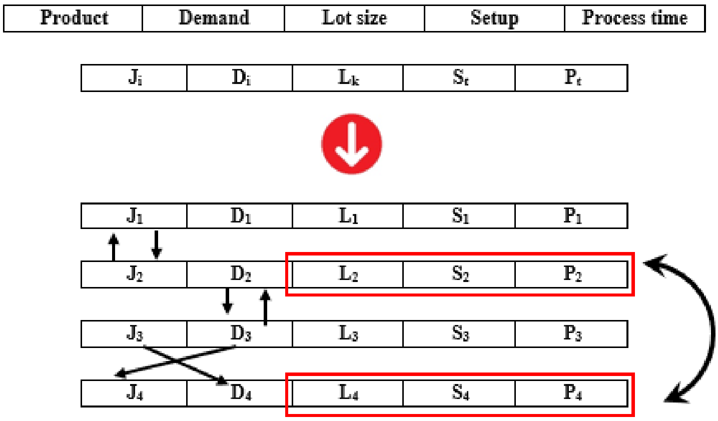


Figure 8: Optimization chromosomes process

The chromosome configuration that was implemented is as follows:

- Chromosome 1: lot J1 for 4 weeks loading (L1)
- Chromosome 2: lot J2 for 4 weeks loading (L2)
- Chromosome 3: lot J3 for 4 weeks loading (L3)
- Chromosome 4: lot J4 for 4 weeks loading (L4)
- Chromosome 5: sequence load for week #1 (D1)
- Chromosome 6: sequence load for week #2 (D2)
- Chromosome 7: sequence load for week #3 (D3)
- Chromosome 8: sequence load for week #4 (D4)

The chromosome boundaries for the production lot, represented as integers, as follows:

- Constraints 1: $\mathbf{1} \leq \mathbf{L1} \leq \mathbf{16}$; C1 = $\sum_1^4 \mathbf{Ln} \leq \sum \mathbf{J1}$
- Constraints 2: $\mathbf{1} \leq \mathbf{L2} \leq \mathbf{27}$; C2 = $\sum_1^4 \mathbf{Ln} \leq \sum \mathbf{J2}$
- Constraints 3: $\mathbf{1} \leq \mathbf{L3} \leq \mathbf{27}$; C3 = $\sum_1^4 \mathbf{Ln} \leq \sum \mathbf{J3}$
- Constraints 4: $\mathbf{1} \leq \mathbf{L4} \leq \mathbf{12}$; C4 = $\sum_1^4 \mathbf{Ln} \leq \sum \mathbf{J4}$
- Constraints 5: $\mathbf{1} \leq \mathbf{D1} \leq \mathbf{24}$; whereas D1 = integer (1, 2, … 24)
- Constraints 6: $\mathbf{1} \leq \mathbf{D2} \leq \mathbf{24}$, whereas D2 = integer (1,2, ... 24)
- Constraints 7: $\mathbf{1} \leq \mathbf{D3} \leq \mathbf{24}$, whereas D3 = integer (1,2, ... 24)

- Constraints 8: $\mathbf{1} \leq \mathbf{D4} \leq \mathbf{24}$, whereas D4 = integer (1,2, ... 24)

The results of the initial scheduling optimization using GA are shown in Table 3.

Table 3: Result after optimization

Item	Job sequence				Cost of setup and
	Wk1	Wk2	Wk3	Wk4	initial invt. ($)
1	P2(13)	P1(5)	P1(2)	P2(2)	890
2	P4(4)	P4(2)	P4(2)	P4(3)	725
3	P3(9)	P3(11)	P3(7)	P1(5)	443
4	P1(5)	P2(8)	P2(9)	P3(4)	1,245
					3,303
Cost. Inv. ($)	14,015	4,695	1,450	18,565	38,725
Inv. Space ($)					1,000
Cap. Sched ($)					0
Late del. ($)					113
Total ($)					43,140

The graph illustrating the search results from the optimization process by GA is shown in the following Figure 9.

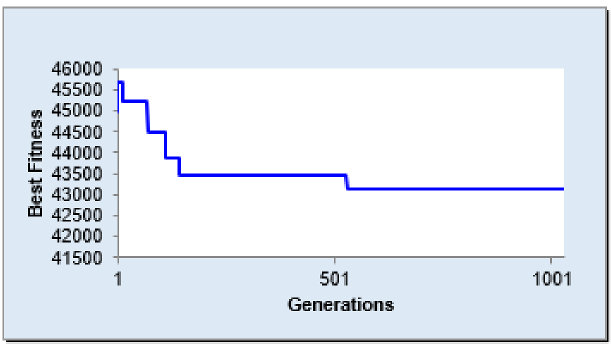


Figure 9: GA Fitness generation

5. DISCUSSION

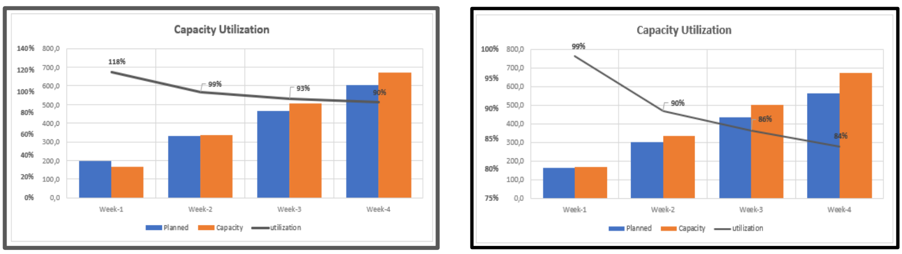
In job shop scheduling, inventory results from determining the lot sizes or batches required to complete a job on a machine. The presence of multiple setups affects both the amount of inventory generated and the job completion time for each lot or batch. Determining the appropriate lot number not only helps manage existing inventory and available capacity but also ensures timely delivery as desired by the customer.

The optimization results indicate that proper lot determination can minimize total costs, especially when considering delivery delays to customers. The scheduling optimization results are presented in Table 4 below.

Table 4: Initial loading and requirement

Product	Week 1		Week 2		Week 3		Week 4	
	Load	Req	Load	Req	Load	Req	Load	Req
1	5	6/16	5	7/16	2	9/16	5	16/16
2	13	12/27	8	16/27	9	20/27	2	27/27
3	9	10/27	11	14/27	7	18/27	4	27/27
4	4	3/12	2	6/12	2	7/12	3	12/12

The results show that optimization with genetic algorithms (GA) not only prevents delays in product due dates but also optimizes lot sizes and work sequences, enhancing the utilization of available production capacity in each period. The comparison of capacity utilization between the initial and optimized results is illustrated in the following Figure 10.



(a) (b)

Figure 10: Capacity Utilization; a) Initial FCFS; b) After optimization

Comparing the capacity usage in images a and b reveals that in image a, the first week's loading exceeds the available capacity, indicating that some work must be postponed to the following week, potentially affecting the predetermined delivery deadlines. Conversely, in image b, the first week's loading is below capacity, and this is similarly true for weeks 2, 3, and 4. This happens because the sequence of machine processes changes after the genetic algorithm optimization process. The changes to the loading sequence on the machine for each week are as follows: In week 1, the sequence changed from 1-2-3-4 to 2-4-3-1; in week 2, it changed to 1-4-3-2; in week 3, it changed to 1-4-3-2; and in week 4, it changed to 2-4-1-3. Additionally, the Fitness value decreased from $48,519 to $43,140. According to the GA results, the optimal value was reached in the 529th generation and remained constant for 500 generations, with the search concluding in the 1029th generation.

6. CONCLUSION

In job shop scheduling for identical machines, the setup process typically occurs multiple times. Applying lot sizes or batches in processing various products and their variations will impact completion time and create inventory at different stages of the process. This presents a challenge for planners, as finding an optimal schedule is a complex task. One effective method for aiding in the search for optimal values is the genetic algorithm approach, which has been utilized by several researchers, including in this study.

Inventory must be carefully considered, as it is often overlooked. Besides incurring costs, inventory introduces new challenges, such as storage and handling issues, and more importantly, it can pose a significant safety risk in the workplace.

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AUTHOR CONTRIBUTIONS

H. Irwan: Writing – Original draft preparation; M.N.A Rahman: Supervising, writing-review and editing; Z. Ebrahim: Reviewing and editing; R.A.C Leuveano: Optimization input and reviewing; N. R. Dzakiyullah: Software Optimization input and reviewing.

CONFLICTS OF INTEREST

The article has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the article.

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