Original Research

Using Genetic Algorithm and Simulation for Parallel Machine Scheduling in Plastic Packaging Manufacturing

Nara Samattapapong[1*], Jiratsaya Panasri[2]

Received: 27 February 2025 / Accepted: 4 July 2025 / Published online: 4 July 2025

*** Corresponding Author Email, nara.samattapapong@gmail.com**

1, 2- Department of Industrial Engineering, Suranaree University of Technology, Nakhon Ratchasima, Thailand

Abstract
This research focuses on optimizing production scheduling for parallel machines by employing a combination of simulation techniques and Genetic algorithms. The primary goal is to efficiently allocate tasks to the machines, maximize raw material utilization, meet customer delivery deadlines, and minimize overall production time. Through a comprehensive study and data collection of planning and production sequencing in a plastic packaging factory, a significant issue arose in task allocation to machines. This is because there is no systematic study of production sequencing. Currently, production sequencing relies on the experience of planners in the production planning department, and existing production scheduling tools lack the ability to validate the optimal sequencing for achieving the best results. The researchers employed simulation techniques in conjunction with Genetic algorithms to identify the optimal production sequence for the machines, thus maximizing the overall efficiency of the production system's operating time. The experiment's results show that employing simulation techniques and Genetic methods for production sequencing significantly reduces the total running time of the production system. Specifically, it lowered the total running time from the current 251,190.90 seconds to 137,060.10 seconds, resulting in a reduction of 114,130.80 seconds, which accounts for 45.44 percent of the total working time.

Keywords - Simulation technique; Production sequence; Parallel machine; Genetic algorithm

INTRODUCTION

In the business world, the plastic product industry holds a significant role in the Thai economy due to its substantial contribution to added economic value. Currently, there is anticipation of heightened competition within the plastic product industry. It is predicted that sales of plastic products in the country are likely to increase on average by 2–3 percent per year [1]. In addition, products share similarities with those of competing organizations, making it essential for organizations to adjust their strategies to meet customer demands. Such adaptability is crucial for business survival and enhancing competitiveness.

Several significant factors impact production and business operations, including costs, product delivery times, resources, raw materials, etc. These factors are essential for business operations to achieve their goals. The production planning and scheduling processes thus serve as important tools for effectively managing various production factors and enhancing competitiveness.

This research examines a plastic packaging factory as a case study. This industry primarily caters to customer needs by producing various styles and quantities on the same production line. A key challenge is scheduling parallel production because there are two stamping machines with the same model but different production capacities. The plastic product factory currently faces challenges in its production planning and sequencing processes. There is a lack of a structured approach to production sequencing, with the sequence heavily dependent on the experience of the planning staff in the production planning department and primarily driven by customer delivery deadlines. Consequently, the utilization of raw materials falls short of the organization's objectives.

It was also discovered that the existing production scheduling tool in Microsoft Office Excel is ineffective. This is due to its inability to verify whether the current production planning and sequencing processes are yielding suitable results. Hence, this research was undertaken to streamline production schedules on parallel machines by integrating simulation techniques with the Genetic algorithm. This involved employing a simulation program called Flexsim to assess the product's machining capabilities and machine productivity. The Flexsim software offers user-friendly tools for obtaining solutions without the need for complex coding, unlike some other software programs. It allows for adjustments based on the real production system's conditions and constraints, enabling efficient tailoring of conditions to optimize the production sequencing process. The ultimate goal is to ensure timely delivery to customers while minimizing the total working time.

THEORETICAL UNDERPINNING AND HYPOTHESES

I. Related Theories

Production scheduling is a critical decision-making process that involves allocating tasks to limited resources, including staff, machinery, equipment, and the time required for task execution. This process holds significant importance within the manufacturing industry [2]. Production scheduling is a complex process that varies depending on the nature and characteristics of the product being manufactured. As a result, organizations must seek suitable techniques and methods, as production scheduling directly impacts their ability to meet customer demands [3]. This research focused on the production scheduling of parallel machines with identical operational characteristics and work formats but differing production rates [4]. Genetic methods, a way to find the best solutions in large datasets, are used alongside computer simulation, which mimics the functioning of various systems like industrial production and transportation [5]. The goal is to analyze current operations, identify opportunities for improvement, and discover the most efficient methods without causing an impact on actual operations [6].

Parallel machine production scheduling is a problem involving variables like the number of tasks, production times, and delivery schedules for various customers [7]. Another important factor to consider is the constraints of the current production machinery. These machines' performance can vary depending on a number of variables, including their lifespan and technology [8]. If the efficiency of the parallel machines used in production varies, it can lead to differences in the working times of the production system, potentially resulting in production falling short of meeting customer demand. As a result, parallel production scheduling of machines necessitates the use of effective tools in order to respond to customer demands on time.

II. Related Studies

Caputo et al. [9] introduced a simulation model to assist with production scheduling, utilizing the OptQuest for Arena software to analyze potential sequences in the production process. The process starts by assigning resources to various workstations using VBA code in the database. After that, the data is used to simulate production and find the most cost-effective production order. The study showed that Arena software can analyze optimal production schedules.

Cheng and Chan [10] introduced a simulation model to assist in production planning, aiming to minimize the total working time. They achieved this using the Flexsim simulation program. The process began with the processing of production data from a Microsoft Office Excel spreadsheet. Within the Flexsim simulation model, data was grouped, and priority was given to the data group with the highest slack time for production sequencing. The simulation revealed that optimizing production sequencing reduced slack time but also increased the processing time needed to find the optimal solution.

Savas Balin [11] employed a Genetic algorithm to schedule the parallel production of machines with identical operational characteristics but different sizes. To minimize the total working time of the production system, a new Genetic crossover method was devised to enhance efficiency. This novel method was tested using simulation software to obtain results. The results obtained from the experiment were subsequently compared with the Longest Processing Time (LPT) method to assess the efficiency of the new approach. The experimental findings demonstrate that the Genetic algorithm can effectively reduce the total work time, even when dealing with large problem sizes.

Wasapon Tharana et al. [12] devised a production scheduling method with the aim of minimizing the total working time. This method involves two key steps: 1) grouping work into clusters using mathematical models to allocate tasks to machines optimally; and 2) work sequencing, which employs heuristic techniques. In this sequence, priority is given to tasks with the earliest due dates and those requiring the least amount of time. The study revealed that this production scheduling method can enhance efficiency by 7.83 percent compared to old production scheduling.

Suebphong Saengudorn and Teeradej Wutthiphonphan [13] utilized a hybrid Genetic algorithm for production scheduling in the automobile manufacturing industry to minimize total costs arising from job delays and remaining work in the system. They implemented this approach using Visual Basic in conjunction with the Mathlab program. The process begins by creating an initial population of 5 chromosomes. This initial population consists of 2 randomly selected chromosomes and 3 chromosomes generated through heuristic methods: Earliest due date (EDD), Shortest processing time (SPT), and Minimum slack time (MST). The next step involves calculating the fitness value based on the objective equation and selecting chromosomes using the roulette wheel method. Then random positions were performed to swap the chromosomes, and the best chromosomes were selected to be used as the starting population in the next round. The experiment's results show that the hybrid Genetic algorithm-based production scheduling method can reduce the overall cost associated with delayed work.

Thanawat Wongkruea and Worawut Wangwatcharakul [14] introduced a production scheduling method aimed at optimizing the number of machines used, increasing machine utilization efficiency, and reducing the total cost of the production system. This method utilizes a mathematical model to determine the optimal solution and combines heuristics with production scheduling techniques. The result demonstrated that production scheduling using mathematical models yields superior results compared to the current combination of heuristics and production scheduling methods. This approach can cut the overall system costs by 13.43 percent compared to the current method.

Reviewing the related literature reveals that the production scheduling problem for parallel machines has garnered significant attention. Various methods, including Genetic algorithms and simulation techniques, have been employed to minimize total working time and find suitable solutions. However, this study utilized the Flexsim simulation program in conjunction with Genetic methods to determine the optimal production sequence for parallel machines. In particular, in the context of plastic packaging factories, it was found that no previous research had examined this specific production scenario. Hence, this research employed the Flexsim simulation technique in conjunction with Genetic methods to schedule the production of parallel machines based on product pair formation. It aimed to optimize machinery productivity and determine the production sequence on the machines, all within the specific conditions and constraints of the plastic packaging factory.

RESEARCH METHODOLOGY

The operational process began with a study of the process, followed by the planning and sequencing of production. Subsequently, the current operational characteristics were analyzed, and data related to the production sequencing process was collected. The collected and analyzed data were then used to establish the current production sequencing model. Next, the model's accuracy and validity were verified, and the production sequencing process was designed. This design considered various factors within the production process and utilized Genetic algorithm in combination with simulation techniques to determine the optimal production sequence. After that, the experiment's results would be analyzed and summarized as shown in Figure 1.

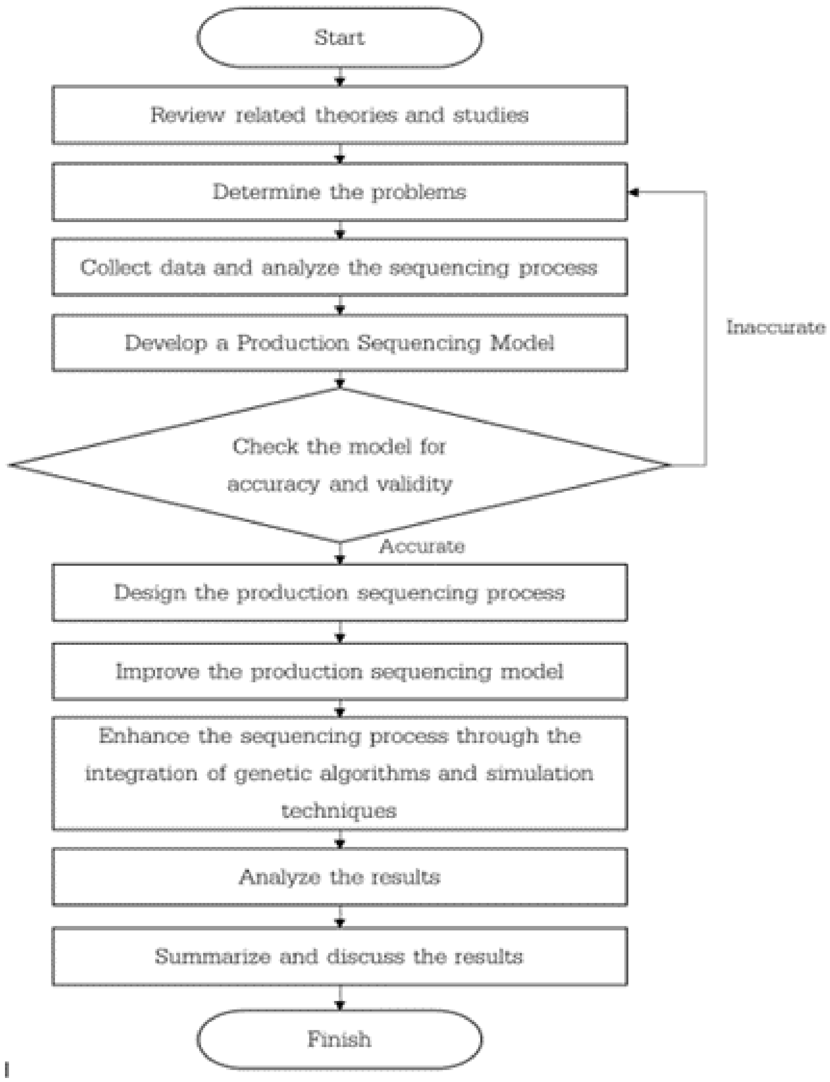

FIGURE 1
RESEARCH PROCEDURES

I. Analyzing the Plastic Packaging Factory's General Characteristics

The plastic packaging factory currently plans and schedules production based on customer delivery schedules and the expertise of its planning department staff for meeting customer requirements punctually. The process began by receiving customer orders, followed by recording the production quantities using the "Master List" on Microsoft Office Excel. After that, the production planning department developed the production sequence, prioritizing product delivery schedules and taking into account similar mold sizes. Then the production planning department inspected the production materials. In the case of insufficient production materials, the production planning department prepared materials of similar sizes to the production plan. Afterward, they recorded the production sequencing plan and transmitted it to the production department to ensure timely production in alignment with the customer's delivery schedule.

II. Collecting Data and Analyzing the Sequencing Process

The data collection for the production sequencing process began with meetings involving individuals knowledgeable about the factory's production processes. During these meetings, researchers inquired about the sequencing process, production factors, and machinery limitations. Furthermore, the researcher requested product samples that had been manufactured for customers to use in the research. A total of 30 product samples were obtained for the experiment, as this represented the largest feasible number for scheduling production in a single day out of the total of 1,145 product types produced by the case study factory.

III. Developing a Production Sequencing Simulation Model with Flexsim

In order to create a simulation model for a production sequencing process using Flexsim, it started by defining the basic units to be used in the model and then preparing the machines and tools required for the experiment. Finally, researchers input the production process parameters into the simulation model to make it operate according to the current production conditions as shown in Figure 2.

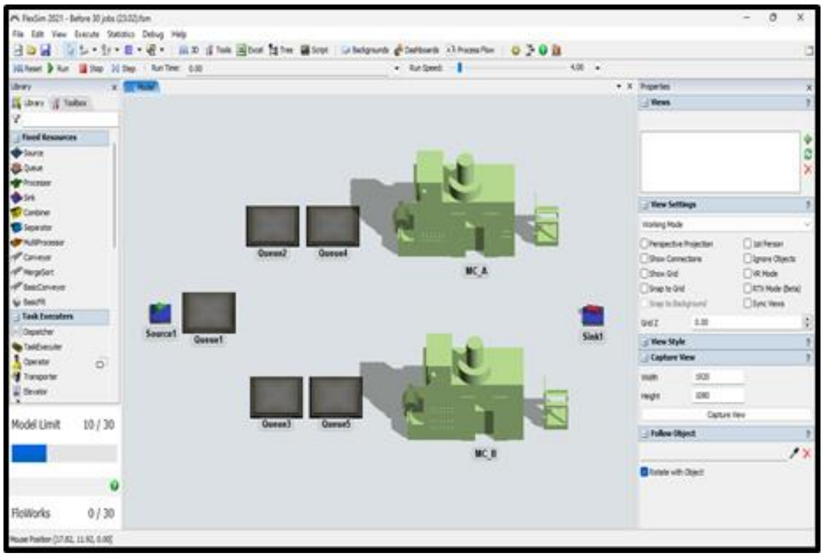

FIGURE 2
MODELING CURRENT PRODUCTION SEQUENCING

IV. Checking the Model for Accuracy and Validity

Before using computer simulations, it's important to validate them. This can ensure the simulation model closely matches actual situations.

The validation results of the simulation model showed that it worked accurately in line with the real conditions of a plastic packaging factory. Moreover, there were no error warnings from the program.

To ensure the model's validity, researchers compared the total working time of the current production sequence with the model. Minitab was used for statistical analysis and calculations. There are two steps to checking the validity.

1) Normality Test of the current production sequence and production process simulation model to determine whether the data sets follow a normal distribution [15]. The test results indicate that the P-value for the current production sequence is 0.704 as illustrated in Figure 3, and the P-value for the production process simulation model is 0.388 as illustrated in Figure 4. Both P-values met the specified significance level of 0.05 in the test, suggesting that the data distribution is normal.

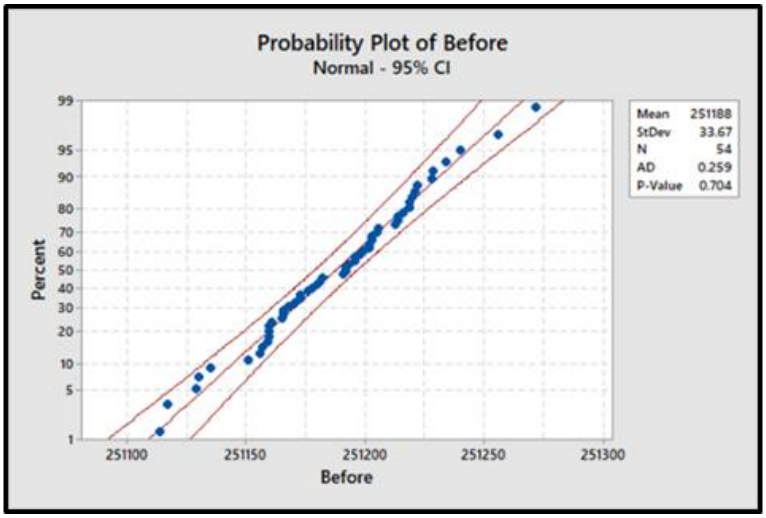

FIGURE 3
TEST RESULTS OF CURRENT SEQUENCING

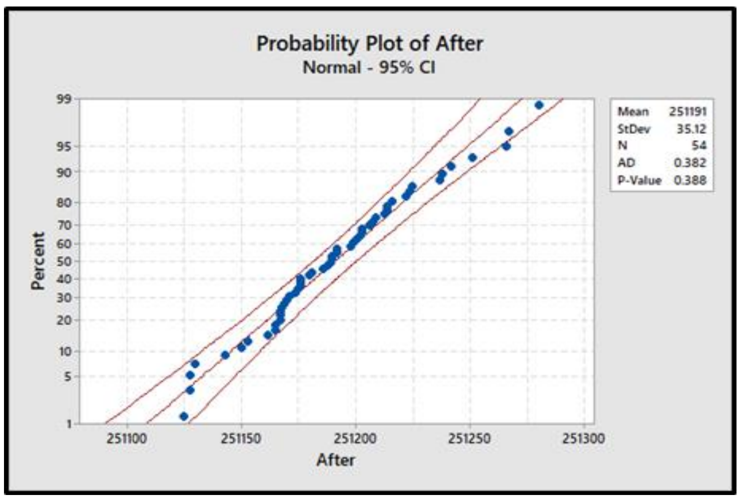

FIGURE 4
TEST RESULTS OF THE SIMULATION MODEL

2) a Paired T-Test was conducted to compare the simulation model with the current production sequencing process. This aimed to determine if the simulation model accurately represents the current production sequencing process. The test results indicated a P-value of 0.643 as shown in Figure 5, which exceeded the predefined significance level. Therefore, the production sequencing process model created is valid and can represent the operation of the current production sequencing process.

Test

Null hypothesis	H_0: μ_difference = 0
Alternative hypothesis	H_1: μ_difference ≠ 0

T-Value	P-Value
-0.47	0.643

FIGURE 5
RESULTS OF THE COMPARISON BETWEEN THE MODEL AND THE CURRENT SEQUENCE

V. Designing the Production Sequencing Process

Designing the planning and sequencing process aims to optimize raw material utilization, ensure timely product deliveries, and minimize overall working time. This process involves three key steps.

Step 1: Pairing Product Compatibility

The first step focuses on optimizing raw material utilization. This involves considering various factors in the production process:

- Ensure the materials are of the same type.
- Match the thickness of the materials.
- Keep the height of the molds within a 2-fold difference.
- Confirm that there is sufficient mold space to enable simultaneous production on the same machine.

Step 2: Machine Capacity Assessment

In this step, researchers assessed the production capacities of two stamping machines, namely Machine A and Machine B, in our case study factory. These machines have similar operational characteristics but differ in their production rates, which affect their productivity. The decision regarding which machine to assign work to is based on input data related to the printing area of Machine B. Machine B can handle tasks that were originally designated for Machine A. Specifically, work is assigned to Machine B when the mold area is either larger or smaller than the printing area of Machine B. Production takes place on Machine B only when the mold area is smaller than the printing area of Machine B.

Step 3: Work Allocation to Machines

This step is crucial because the order in which tasks are assigned to machines impacts both the overall working time of the production process and the delivery schedule to various customers. Consequently, careful consideration is given to the sequence of work, taking into account the specific conditions and constraints within the plastic product factory.

VI. Improving the Production Sequencing Model

It was confirmed that the model effectively mirrored the real production sequencing process. Consequently, enhancements were made to the production sequencing process by developing an algorithm within the program. This algorithm aimed to utilize the findings from the design of the production sequencing steps outlined in Step 1 (product forming ability) and Step 2 (machine production ability).

VII. Enhancing the Sequencing Process through the Integration of Genetic Algorithms and Simulation Techniques

Enhancing the work sequencing approach through the integration of Genetic algorithms and simulation techniques involves two primary steps: 1) Work Grouping: When processing the Flexsim program, it generates all possible work groups. Following the production planning design process, which considers product pair formation capability and machine work productivity capability, these work groups are further subdivided into sub-work groups based on their production capacity. The subgroups are categorized into two: those capable of producing only one machine and those capable of producing two machines. These subgroups are then subjected to further analysis, aiming to determine the sequence of work that minimizes the total working time. This optimization is achieved using a Genetic algorithm implemented through VBA code within the Microsoft Office Excel program. And 2) Sequencing tasks on machines using Genetic methods, comprising the following steps:”

Step 1: determining the population size
Step 2: creating the initial population
Step 3: defining the objective equation
Step 4: evaluating the objective function
Step 5: calculating the fitness value
Step 6: calculating the probability of the initial population
Step 7: selection using the roulette wheel method
Step 8: generating a new population using crossover methods
Step 9: repeating steps 2 to 8 until a suitable solution is achieved, terminating the search
Step 10: obtaining the optimal workflow and minimizing total processing time

RESULT

In a production sequencing experiment that integrated a simulation program with a Genetic algorithm, three production sequencing steps were designed. These steps focus on factors and constraints related to product forming capability, machinery productivity, and the allocation of work to machines. The experiment involved 30 order samples and utilized two production machines.

Step 1: Using the Flexsim program, samples were able to organize a total of 19 workgroups. For instance, Product 1 cannot be molded together with any other product, so it is placed in Work Group 1. On the other hand, Products 4, 5, and 13 can be molded simultaneously on the same machine, and they are grouped into Work Group 4, and so on, as illustrated in Table I.

TABLE I
THE OUTCOME OF THE DECISION MADE IN STEP 1

Work Group	Type	Time (second)	Number of Cavity	Production Quantity
1	1	19.20	1	100
2	2	18.50	3	1,500
3	3	18.50	3	1,500
4	4, 5, 13	20.00	10	1,600
5	6	16.60	3	6,000
6	7, 17	25.80	3	2,500
7	8	23.00	4	1,000
8	9, 10	18.00	2	200
9	11, 18	16.00	8	2,700
10	12, 15, 16	17.00	10	1,600
11	14	20.60	8	6,850
12	19	13.80	2	500
13	20	22.10	3	1,300
14	21, 22	24.10	2	200
15	23, 29, 30	20.70	5	3,470
16	24, 25	20.70	2	1,100
17	26	15.30	1	1,100
18	27	25.00	2	2,000
19	28	16.00	1	1,000

Step 2: Taking into consideration various factors and production constraints, it was determined that work groups 2, 3, 4, 10, 11, and 13 are limited to production on Machine A, while work groups 1, 5–9, 12, 14, and 19 can be produced on both Machines A and B. In Table II, the number ‘1’ indicates work groups that can be produced on the respective machine, and ‘0’ indicates those that cannot. The machines under study are all vacuum-forming machines within the factory, with two machines identified. Although these machines possess distinct production capabilities, they share identical operational characteristics.

TABLE II
THE OUTCOME OF THE DECISION MADE IN STEP 2

Work Group	Active Machinery	
	Machine A	Machine B
1	1	1
2	1	0

3	1	0
4	1	0
5	1	1
6	1	1
7	1	1
8	1	1
9	1	1
10	1	0
11	1	0
12	1	1
13	1	0
14	1	1
15	1	1
16	1	1
17	1	1
18	1	1
19	1	1

Step 3: Allocation of work groups to machines: the 19 work groups obtained from Step 2 were categorized into six subgroups, with each subgroup containing 3–4 work groups. Categorization is based on the production capabilities of the machines. Flexsim program calculates the total working time for each sub-work group, the results are presented in Table III, where '1' signifies work groups that can be produced on a particular machine and '0' signifies work groups that cannot be produced on that machine.

TABLE III
THE OUTCOME OF THE DECISION MADE IN STEP 3

Sub-work Group	Work Group	Active Machinery		Total Running Time (Seconds)
		Machine A	Machine B	
1	2	1	0	28,900.0
1	3	1	0	
1	4	1	0	
2	10	1	0	37,145.0
2	11	1	0	
2	13	1	0	
3	1	1	1	63,837.2
3	5	1	1	
3	6	1	1	
4	7	1	1	20,158.0
4	8	1	1	
4	9	1	1	
5	12	1	1	27,425.8
5	14	1	1	
5	15	1	1	
6	16	1	1	80,015.0
6	17	1	1	
6	18	1	1	
6	19	1	1	

A Genetic algorithm was subsequently employed to identify the optimal production sequence and machine assignments. This was accomplished using a population size of 40 and three rounds to create the initial population. The objective function was then assessed to establish performance indicators for the production scheduling process. After that, the fitness value was computed utilizing the fitness function, and the probabilities of the initial population were determined. These probabilities were used in the selection of parents and the generation of a new population. The outcomes revealed that the best result was achieved during the fourth iteration, resulting in the lowest total working time of 137,082.20 seconds. These findings are summarized in Table IV.

TABLE IV
NUMBER OF BEST RESULTS

Number of Best Results (Times)	Total System Running Time (Seconds)
1	184,285.80
2	168,108.00
3	160,840.20
4	137,082.20

From Table IV, it is evident that finding the best result initially yielded the highest total working time. However, with each subsequent search for the best result, the total working time progressively decreased, ultimately resulting in the most favorable outcome during the fourth attempt, where the total working time reached its lowest value of 137,082.20 seconds. Consequently, this configuration is deemed the most suitable, optimizing the total working time. The production sequence on the machines that leads to the lowest total working time consists of work groups 2, 3, 4, 10, 11, 13, 1, 5, and 6 being processed on machine A. Work groups 16, 17, 18, 19, 12, 14, 15, 7, 8, and 9 are processed on machine B, as indicated in Table 3. When this production sequence, resulting in the lowest total working time, was implemented in the Flexsim program, the total system running time was recorded at 137,060.10 seconds.

TABLE V
EXPERIMENTAL RESULTS

Sub-Work Group	Sequence of Work Groups		Lowest Total Working Time (Seconds)	
	Machine A	Machine B	Machine A	Machine B
1	2, 3, 4	-	28,900.0	-
2	10, 11, 13	-	40,745.0	-
6	-	16, 17, 18, 19	-	80,015.0
5	-	12, 14, 15	-	31,025.8
3	1, 5, 6	-	67,437.2	-
4	-	7, 8, 9	-	23,758.0
		Total	137,082.2	134,798.8

DISCUSSION AND CONCLUSION

This research employed simulation techniques with the Flexsim program in combination with Genetic methods to optimize production sequencing for parallel machines, aiming to achieve the most efficient total working time. Through an examination of the planning and production sequencing processes within a plastic packaging factory, it became evident that there was a lack of systematic study on production sequencing methods. Instead, it relies on the experience of the planning team, and the currently available tools prove to be less effective. Due to the inability to verify the effectiveness of the current planning and sequencing processes, the researcher came up with a 3-step production sequencing approach: forming product pairs, assessing machinery productivity, and assigning tasks to machines. The procedure involves using a simulation program, Flexsim, in combination with a Genetic algorithm to determine the optimal total working time for the production sequence on the machines. This process aims to obtain suitable results and then compare them with the current sequencing method.

The results of testing 30 product samples indicated that work groups can be organized to produce on the same machine simultaneously. After considering various production factors, a total of 19 work groups were identified. These work groups were further divided based on their ability to be produced on the machines, resulting in 6 subgroups, each containing 3–4 groups. This is because each work group can only operate on specific machines. Moreover, the sequence in which work groups are scheduled on the machines has varying effects on the overall system runtime.

Next, a Genetic algorithm was employed with a population size of 40 and conducted over 3 rounds to determine the shortest total running time. The Genetic method yielded the best results during the 4th iteration, resulting in the shortest total working time of 137,082.20 seconds. This was an improvement over the total working time of 137,060.10 seconds obtained through processing in Microsoft Office Excel. The optimized sequence for work groups on machine A was as follows: work groups 2, 3, 4, 10, 11, 13, 1, 5, and 6. On machine B, the work groups were 16, 17, 18, 19, 12, 14, 15, 7, 8, and 9, respectively.

This represents a significant improvement, as it achieved the lowest and most optimal total working time compared to the initial average total working time of 251,190.90 seconds. The current sequencing reduced the total working time to 114,130.80 seconds, marking a notable decrease of 45.44 percent.

Furthermore, this optimization allowed for on-time delivery of products for 27 out of 30 samples, with only 3 samples experiencing delayed delivery to customers. In comparison to the current sequencing process, where 21 product samples could be delivered on time and 9 product samples experienced delays, this represents a significant improvement in meeting customer delivery deadlines. Additionally, when considering the percentage utilization of raw materials resulting from the optimized production sequencing process, the average utilization rate was 99.56 percent. This is a substantial increase from the previous average utilization rate of 77.38 percent, reflecting a remarkable improvement of 28.66 percent.

In summary, this study provided a comprehensive framework for optimizing production sequencing for parallel machines in the plastic packaging industry. The combined use of simulation techniques and Genetic algorithms proved to be a powerful tool for achieving significant improvements in production efficiency, on-time deliveries, and raw material utilization. The findings from this research offer valuable insights and practical applications for similar manufacturing industries looking to enhance their production scheduling processes.

REFERENCES

[1] Plastics Industry Insights Analysis Center, Thai Plastic Industry Structure 2021. Accessed from: http://plastic.oie.go.th/ReadArticle.aspx?id=21857 [accessed on June 13, 2022].APA Citation Style. (2014). Retrieved on July 27 from http://www.apastyle.org/

[2] Sriphol, N. (2017). Scheduling for Number of Tardy Job Improvement: A Case Study. Department of Industrial

[3] Engineering, Thammasat University, Khlong Luang, Pathum Thani.

[4] Kurukidcumchorn, P. (2013). Comparison Unrelated Parallel Machines Scheduling of Result from Scheduling Program and Assignment Problem. Department of Industrial Engineering Management, Silpakorn University, Mueang, Nakhon Pathom.

[5] Chutima, P. (2003). Techniques for Scheduling Operations. Bangkok: Chulalongkorn University.

[6] Thongprasert, S. (2001). Simulation. Bangkok: Chulalongkorn University Printing House.

[7] Jongkol, P. and Paramorn, T. (2010). Run Length Analysis for Queueing Simulation Model. UBU Engineering Journal, 3 (1), 12–19.

[8] Sudpum, N. and Limnorarat, S. (2008). Production Scheduling for Parallel Machines with Dependent Setup Times. In Proceedings of the 46th Kasetsart University Annual Conference: Architecture and Engineering and Natural Resources and Environment, January 29th-February 1st, Thailand, 329–336.

[9] Thongman, P. and Samattapapong, N. (2021). Production Sequence using Simulation Techniques: Case Study of Mineral Production Plants for Dairy Cow. In Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management, Singapore: IEOM Society International, 650–659.

[10] Caputo, G., Mose, G. and Guizzi, G. (2009). Optimization of Production Plan through Simulation Techniques. Wseas Transactions on Information Science and Applications, 3 (6), 352–362.

[11] Cheng, H. C., and Chan, D. Y. K. (2011). Simulation Optimization of Part Input Sequence in a Flexible Manufacturing System. In Proceedings of the 2011 Winter Simulation Conference, edited by S. Jain, R.R. Creasey, J. Himmelspach, K.P. White, and M. Fu, 2374–2382. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

[12] Balin, S. (2011). Non-identical parallel machine scheduling using Genetic algorithm. Expert Systems with Applications, 38 (6), 6814-6821.

[13] Tharana, W., Chukijrungrog, T. and Wiriyaphong, M. (2012). Production Scheduling of Printer Machine in Corrugated Boxes Industry. Conference of Industrial Engineering Network, Phetchaburi: Sripatum University, 339–345.

[14] Sangudon, S. and Wuttipornpun, T. (2012). Application of Hybrid Genetic Algorithms for Assembly Flow Shop Scheduling Problem. The Journal of KMUTNB, 22 (1), 107-117.

[15] Wongkrue, T. and Wangwatcharakul, W. (2021). Parallel Machine Scheduling in the Integrated Circuits Testing Process. Thai Journal of Operations Research, 9 (1), 153–162.