

AN APPROACH TO PRODUCTION SCHEDULING FOR REDUCING CARBON FOOTPRINT IN AN AGRICULTURAL TRANSPORT VEHICLE MANUFACTURING COMPANY: A CASE STUDY IN UTTARADIT PROVINCE

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Abstract

This study investigates a production scheduling problem for an agricultural vehicle manufacturer in Uttaradit Province. The primary goal is to generate an improved production schedule using a mathematical model. The model minimizes the total time required to produce the entire product (the make span) while also tracking the environmental impact of each part (product carbon footprint, CFP). This study created a computer program and used a local search heuristic to find the optimal schedule. The researchers collected data from customer orders and the company's production and maintenance teams. It included information such as the number of machines, the time required to set up each machine, the time needed to produce each product, the electricity used, the waste generated, and the rules and constraints imposed on production. The production scheduling problem was divided into three levels: small, medium, and large, allowing for the determination of the optimal schedule for each scenario. The results show that the mathematical model performs well on all problem sizes. For example, in the small-scale case with six jobs and seven machines, the model took 6,961.23 minutes to compute, which took only 0.214 seconds for all machines to be fully utilised, and the CFP was 91.791 kg of CO₂ equivalent. In contrast, the company's original large-scale schedule took 38,561.12 minutes, or approximately 81 working days, at an 8-hour workday. However, with the revised schedule, the time was reduced to 27,421.18 minutes, or approximately 57 working days, a saving of 24 days. Using this mathematical model, the approach reduced total production time by 11,139.94 minutes, improved efficiency by 28.89%, and lowered the CFP by 497.759 kilograms of carbon dioxide equivalent, thereby achieving the research's primary goal. The proposed approach reduced the total production time by 11,139.94 minutes, improved efficiency by 28.89%, and reduced the CFP by 497.759 kilograms of carbon dioxide equivalent, thereby achieving the primary research goal.

Keywords: Agricultural-Cargo Truck; Makespan; Mathematical Programming Model; Optimization

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Introduction

Nowadays, the Thai economy relies heavily on exports. In B.E. 2024, export values reached 423,309.2 million baht for crude oil, 416,107.2 million baht for machinery and parts, and 383,464.7 million baht for electrical and electronic machines and components (Kasemrat and Kraiwanit, 2025). The growth of domestic industries drove the export value of machinery and parts, which play a crucial role in the national economy. The government has promoted innovation-oriented economic development plans to enhance competitiveness in all dimensions. Currently, amid intense competition across industrial and service sectors, every enterprise focuses on the four M's of business administration: man, method, material, and money, to achieve maximum efficiency. Alongside improving production efficiency, the industrial sector must prioritize environmentally responsible production (Qi *et al.*, 2024), particularly by reducing greenhouse gas emissions generated throughout a product's life cycle. Therefore, evaluating the total amount of greenhouse gases emitted at each production stage has become essential. The 'Carbon Footprint of Product' (CFP) concept now measures and assesses greenhouse gas emissions in carbon dioxide equivalent (CO₂e) units. This metric is increasingly prioritized by factories as a key performance indicator for managing their manufacturing processes (Suryaningrat, 2016; Nguyen *et al.*, 2022; Bilal *et al.*, 2025; Pongsiri *et al.*, 2025; Xinyi and Jianmin, 2025; Chatchaphon *et al.*, 2025). The main objectives of most businesses are to minimize costs and enhance competitiveness while managing resources for maximum value creation. In this study, the researcher selected an agricultural transport vehicle manufacturing company in Uttaradit Province as the case study. Preliminary data revealed that the company produces parts and accessories for agrarian cargo trucks within a 7,180 m² working area divided into three factories, equipped with 28 machines and over 110 instruments.

The company uses job scheduling for production and maintenance operations and assembles all parts according to customer orders using the First-In-First-Out (FIFO) method. However, the spare parts production line lacked a systematic scheduling process and relied mainly on workers' experience. This study led to the inappropriate use of raw materials, machines, tools, and methods, resulting in both direct and indirect costs. The company could not achieve optimal and efficient production scheduling. Additionally, external factors, such as delays in raw material

delivery and managerial decision-making, further affected production timelines, ultimately resulting in customer delivery delays. Consequently, unexpected costs and potential customer loss occurred. A persistent challenge in many factories remains the lack of a concrete system for collecting and evaluating the Carbon Footprint of Product (CFP) (Pongsiri *et al.*, 2025; Ma *et al.*, 2025), hindering effective monitoring and control of greenhouse gas emissions. This lack of systematic data collection is a key factor preventing production processes from achieving full sustainability and efficiency (Phuk-in, 2022a). Preliminary studies suggested that companies examined and visualized the Carbon Footprint of Products to identify deficiencies in their manufacturing systems in this dimension.

The objective of this research was to apply a mathematical programming model to solve production scheduling problems, optimize production processes, minimize makespan, and measure the Carbon Footprint of Product (CFP) values in a case study of an agricultural transport vehicle manufacturing company in Uttaradit Province.

Materials and Methods

Scheduling Problem

The scheduling problem (Frisch *et al.*, 2021) is a crucial issue frequently encountered in the production industry. Factories aim to develop production plans that maximize efficiency while operating under various regulations and constraints (Cordeau *et al.*, 2000; Cordeau *et al.*, 2001), such as time limitations, machine capacity, and human resources. Properly organized production scheduling allows for optimal coordination among these factors, ensuring timely delivery to customers (Chaouch *et al.*, 2021). Achieving such efficiency is a fundamental goal for all businesses, particularly when integrated with environmentally sustainable production practices (Cordone and Hostens, 2019; Lu *et al.*, 2025; Tariq *et al.*, 2024).

In general, production types can be classified by product characteristics, such as make-to-stock, make-to-order, assembly-to-order, and engineering-to-order, each with distinct features that vary based on customer requirements. Furthermore, researchers can categorize production systems by their operational structure, including mass production, job shop, made-to-order, made-to-stock, assembly-to-order (Frisch *et al.*, 2021), project manufacturing

(Che *et al.*, 2021), batch production, line-flow or assembly, repetitive production (Sarakhsi *et al.*, 2016), and continuous or continuous-flow production. Its system design and output volume define each production type. For instance, make-to-order production primarily depends on specific customer demands, often involves high product variety, and operates in batches. Machines typically run continuously until they complete a production lot and then transition to a new product using the same equipment (Umam *et al.*, 2021; Mou *et al.*, 2025; Phuk-in, 2022b).

The results from the literature review indicated that production scheduling serves various objectives, including: (1) reducing waiting time in the production process, which refers to minimizing the average idle time when machines or workers are occupied with other tasks (Frisch *et al.*, 2021); (2) minimizing work delays, as delay penalties can occur, and the goal is to lessen the overall delay duration or the number of delayed jobs (Aloui and Hamou, 2021); (3) reducing the total cost of the system, which includes both early completion costs and delay costs (Ebrahimi *et al.*, 2020); (4) minimizing the mean flow time within the system (Ebrahimi *et al.*, 2020); (5) determining the makespan range by calculating the maximum and minimum machine completion times; (6) minimizing the overall makespan of the system; and (7) enhancing the environmental efficiency of the production process by aiming to reduce greenhouse gas emissions and the Carbon Footprint of Product (CFP) to the lowest possible level, an essential approach toward sustainable industrial development (Che *et al.*, 2021; Sarakhsi *et al.*, 2016; Park *et al.*, 2025; Bilal *et al.*, 2025; Chatchaphon *et al.*, 2025).

In the study of complex manufacturing processes with large-scale problems, particularly in make-to-order industries, heuristic methods have been applied to address highly constrained, challenging problems. For example, the research of Aloui and Hamou (2021) proposed a heuristic approach to solve additive manufacturing scheduling problems under technological constraints, and the work of Ebrahimi *et al.* (2020) aimed to reduce total energy costs and late penalties in scheduling and placement problems in scheduling systems by comparing the performance of four metaheuristic algorithms. Both studies demonstrated that heuristic methods provided efficient manufacturing scheduling solutions, while also reducing costs and improving energy management efficiency.

Furthermore, the Local Search Heuristic is a popular approach for solving scheduling problems and reducing energy costs. It can provide high-quality solutions through incremental

improvements, as shown in the research of He *et al.* (2024), which focused on energy cost reduction, and the work of Puchinger *et al.* (2022), which used carbon dioxide (CO₂) emissions as the primary criterion for evaluating environmental impact, coupled with improving scheduling speed efficiency, to reduce overall fuel consumption in waterway networks. These studies demonstrated that this method yields satisfactory results.

Company's General Conditions

The case study focuses on an agricultural transport vehicle manufacturing company located in Mueang District, Uttaradit Province, established in 2014. The company produces agricultural cargo vehicles, including pick-up trucks, hydraulic trucks, and agrarian cargo trucks, with an annual production capacity of 75 vehicles and yearly sales of 30,156,000 baht. The organization consists of seven key departments: marketing, production and maintenance, inventory storage, purchasing, finance and accounting, and the board of directors. All departments operate collaboratively in a circular flow system, as illustrated in Figure 1. The board of directors is positioned at the center of this organizational structure, responsible for overseeing operations and for systematically and continuously responding to production and after-sales service requirements.

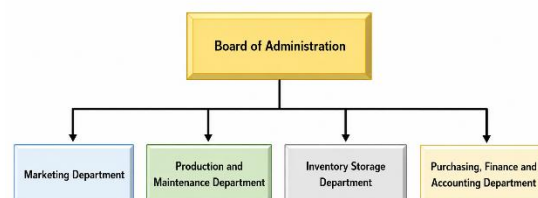


Figure 1. The Organization Chart of a case study of an agricultural transport vehicle manufacturing company in Uttaradit province

The case study company, an agricultural transport vehicle manufacturer located in Uttaradit Province, operates under a made-to-order integrated make-to-stock production system, characterized by initiating production only after receiving customers' purchase orders. The factory utilizes various types of machinery, including cutting machines, turning machines, welding machines, Computer Numerical Control (CNC) machines, vertical milling machines equipped with jigs and fixtures, and drilling machines. A diverse range of products is manufactured, such as 50-mm booth sets, front

assembly sets, pulley sets, chock bolt sets, and 25-mm bolts, as illustrated in Figure 2.



Figure 2. Products of a case study of an agricultural transport vehicle manufacturing company in Uttaradit province

The production line operations are carried out according to monthly orders from the production department, beginning with the procurement of raw materials and proceeding through cutting, forming, inspection, storage, and assembly, as illustrated in Figure 3. The following section describes the detailed steps of the production process:

1. Procurement of raw materials used in production
2. Cutting Process - Cutting cold-drawn bars and steel plates according to production orders.
3. Turning process - to turn the workpiece in various methods as follows;
 - 3.1. Facing turning - to reduce the length of the workpieces that are slightly longer than the final piece and make a smooth surface,
 - 3.2. Parting turning - to reduce the sizes of the workpieces by their patterns,
 - 3.3. Threading turning - to cut threads in the outer surface that make them turn in tightly with knots,
 - 3.4. Boring turning - to make holes in the workpieces in a wide range of diameters,
 - 3.5. Sharpening turning - to clear unexpected sharp scrap of the workpieces,
4. Drilling process – to drill the workpieces, follow the work patterns.
5. Making a tap screw - the process followed both metric and British systems after boring and turning.
6. Welding process - to weld using an electric welding machine called arc welding
7. Roll bending process - to roll pieces of steel plate that were cut, into the wide diameter set in the pattern; and
8. Cleaning, coating, and inspection processes for storage.

Figure 3 shows some workpieces after the turning processes.



Figure 3. Workpieces after turning processes

The parts production process is based on an integrated hybrid make-to-order and make-to-stock system. Most components, such as the 50-mm booth set, front assembly set, pulley set, chock bolt set, and 25-mm bolts, are produced sequentially under precedence constraints, as illustrated in Figure 4.

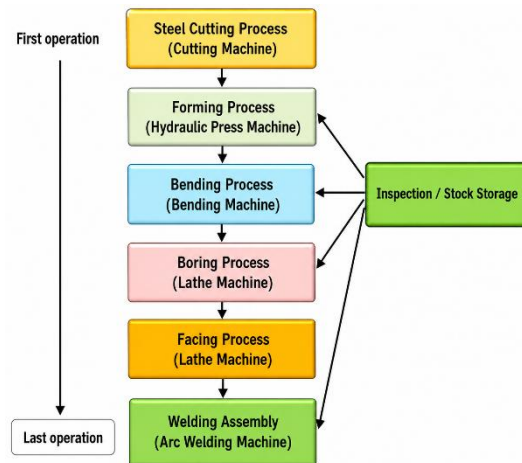


Figure 4. The Operations of the Production Process

The production process steps, illustrated in Figure 4, consist of six stages: cutting, press-forming, roll-bending, boring, turning, and facing/sharpening, and welding. Each stage is assigned specific setup and processing times for each machine, including both operation and maintenance periods. However, the total duration depends on the production volume. For orders exceeding 50 pieces, the company must include an additional maintenance process. The entire production process has not yet recorded Carbon Footprint of Product (CFP) values.

Production time data were collected for each machine involved in the process (Khamphrommi *et al.*, 2019; Frisch *et al.*, 2021; Che *et al.*, 2021;), recognizing that not all operations could be performed on the same machine due to capacity constraints. In the process chart, a slash sign (/) indicates that a machine is capable of performing the required operation, while a blank cell denotes that the machine is unsuitable for that task (Lu *et al.*, 2025; Park *et al.*, 2025). Additionally, CFP data were gathered for each machine used in the production process to support environmental impact analysis.

Standard Production Time – The researchers conducted a time study based on the company’s production reports (Khamphrommi *et al.*, 2019; Frisch *et al.*, 2021; Lu *et al.*, 2025). The production times of each product were analyzed, noting that the company’s machines had been operated primarily based on workers’ experience. Consequently, no complete time-use data were available for all products and processes. This study began by systematically recording time-use data for each process, repeating each measurement 20 times and calculating the average operating time for every step. In addition, setup times for each machine and maintenance stoppages were collected. Although machines of the same type were used, their setup times varied due to different operating conditions.

Therefore, the average setup and operation times were computed and utilized for analysis, as presented in Tables 1 and 2.

Data Collection of the Carbon Footprint of Product (CFP)

The data collection process for evaluating the Carbon Footprint of Product (CFP) encompasses measurements across all stages of the production lifecycle, from raw material procurement and manufacturing processes to electricity consumption within the production facility. The assessment includes data on machine horsepower (Hp) and electrical energy usage. Additionally, it covers the transportation of raw materials and finished goods, the utilization of manufactured components, and waste management activities such as disposal, recycling, and upcycling. All collected data are systematically compiled, analyzed, and used to calculate and evaluate the product’s total carbon footprint, as presented in Tables 2 and 3.

The table presents data collected on the operation of machinery used in the production of components for the case study of an agricultural transport vehicle manufacturing company in Uttaradit Province. The study recorded production time for each machine, along with the corresponding horsepower (Hp) utilized during operation. Additionally, the study gathered data on maintenance time and information on waste

Table 1. Sample of setting machine ability for producing a 50-mm booth set

Parts	Process	Machine Number:						
		1	2	3	4	5	6	7
50 - mm booth set	1.Cutting	/	/					
	2. Facing Turning			/	/			
	3. Boring Turning			/	/			
	4.Sharpening Turning			/	/			
	5. Drilling					/	/	
	6. Tapping Screw							/
Inspection CFP/ Maintenance (for quantities over 50 pieces)		/	/	/	/	/	/	/

Table 2. Sample of adjusting time and Operating time of the machine for producing a 50-mm booth

Parts	Process	Production Time (Minutes)				No. of order (pieces)
		Adjusting Time (S)		Maintenance Time (S)	Operating Time (P)	
50 - mm booth set	1.Cutting	1.45	1.51	5.51	28.48	65
	2.Facing Turning	6.11	6.84	3.50	17.53	65
	3.Boring Turning	10.11	8.36	2.59	30.31	65
	4. Sharpening Turning	5.35	5.25	2.58	9.15	65
	5.Drilling	5.29	5.24	5.20	5.33	65
	6.Tapping Screw	3.12	3.15	2.00	5.09	65
Collection of CFP Data on Electricity Consumption		/	/	/	/	/

generated throughout the production process, including production scraps, metal shavings from turning, and drilling debris. The data collection also covered the storage of finished components intended for subsequent assembly and use, as detailed in Table 3.

Table 3. An Example of Carbon Footprint (CFP) Calculation Based on Machine Operating Time for the Production of 50 mm Booth Components

Serial No.	Data Item	Emissions (kg CO ₂ e)
1.	Sourcing of Raw Materials	0.225
2.	Cutting	4.642
3.	Facing Turning	31.431
4.	Boring Turning	49.406
5.	Sharpening Turning	2.983
6.	Drilling	2.606
7.	Tapping Screw	0.498
Total Carbon Footprint (CFP)		91.791

From the table presenting the calculation of the Carbon Footprint of Product (CFP) for the production process of 50-mm booth components, each production activity utilizes three main types of energy, including fuel energy and electrical energy associated with operating time, and waste generated from the production process, all of which are considered in the CFP assessment. The calculation results revealed that the production of these components generated a total carbon footprint of 91.791 kgCO₂e.

Manufacturing orders data – The production department received manufacturing orders from the production planning department, which included item numbers and quantities for each product. This study focused on the production of five key components: the 50-mm booth set, the front assembly set, the pulley set, the chock bolt set, and the 25-mm bolts. The company produced the quantities of each part according to the customer orders placed in October 2024. During this period, the customer demand volumes were relatively similar, directly and intricately influencing the production scheduling process. Therefore, ensuring the accuracy of order data was essential for effective production planning. Table 4 presents a sample of the production orders for October 2024.

Table 4. Sample of order items to produce of October, 2024

Order Items	Quantity (pieces)
50-mm booth set	65
Gear Boost Set 203	50
Front Beam Lock Pin	220
25-mm bolts	200
front-assembly set	120
29 mm. Shaft Pin (6203)	50

Mathematical model – The proposed mathematical model is presented in this section (Frisch *et al.*, 2021; Khamphrommi *et al.*, 2019 ; Bilal *et al.*, 2025). The researcher compiled the necessary operational data from the company and formulated the model by defining its indices, parameters, decision variables, objective function, and constraints, as described below:

Indices

i = work order, where $i = 1, 2, \dots, n$

j = machine order, where $j = 1, 2, \dots, m$

Parameters

n = number of works

m = number of machines

PO_i = quantity of production order of work i (pieces)

PW_{ij} = used time of producing work i with machine j (min/piece)

TTP_{ij} = total used time of producing work i with machine j (min)

ST_{ij} = setting-up time of machine j for work i (min)

M_{ij} = maintenance used time of machine j for work i (min/time)

QM_j = quantity of work i in maximum, then maintain machine j (piece)

T_j = numbers of machine j maintenance (times – integer)

TC_j = total used time of the operation with machine j (min)

AM_{ij} = the matrix of the work i at the j operating machine

STM_{ij} = start time of machine j for work i

EF_{ij} = carbon footprint emissions (kgCO₂e) of machine j for job i based on operating time

C_{max} = maximum time of makespan of any machine

Decision variable

$X_{ij} = 1$ (assign work i to machine j), and 0 (do not assign work i to machine j)

Objective function

The objective of the mathematical model developed for production scheduling under the factory's real operating conditions is to minimize the total makespan (Z). The model formulation aims to achieve optimal scheduling efficiency by reducing the overall completion time of all jobs in the production system, as expressed in the following equations (Khamphrommi *et al.*, 2019; Chaouch *et al.*, 2021; Phuk-in, 2022a,b; 2024a,b; Lu *et al.*, 2025).

$$\text{Minimize } Z = C_{max} \quad (1)$$

Where,

$$C_{max} = \text{Max} \{TC_j\} \quad (2)$$

$$TC_j = \sum_{i=1}^{i-1} X_{ij} [(PW_{ij} PO_i) + ST_{ij} + (M_{ij} T_j) + EF_{ij}]; \quad \forall j \quad (3)$$

Constraint functions

$$\sum_{j=1}^m X_{ij} \leq \sum_{j=1}^m X_{(i-1)j}; \quad \forall i; i \geq 2 \quad (4)$$

$$\sum_{j=1}^m X_{ij} = 1; \quad \forall i \quad (5)$$

$$\sum_{i=1}^n X_{ij} [PO_i / QM_j] = T_j; \quad \forall j \quad (6)$$

$$STM_{ij} \geq \sum_{i=1}^{i-1} TTP_{ij}; \quad \forall i, \forall j; i \geq 2 \quad (7)$$

$$TTP_{ij} = [(PW_{ij} PO_i) + ST_{ij}] X_{ij}; \quad \forall i, \forall j \quad (8)$$

$$AM_{ij} X_{ij} = 0; \quad \forall i, \forall j \quad (9)$$

$$STM_{1j} = 0; \quad \forall j \quad (10)$$

$$X_{ij} \in \{0,1\}; \quad \forall i, \forall j \quad (11)$$

$$M_{ij} T_j < TC_j; \quad \forall i, \forall j \quad (12)$$

$$EF_{ij} < TC_j; \quad \forall i, \forall j \quad (13)$$

According to the equations above, equations (1)-(3) define the objective function to minimize the makespan. Inequality (4) represents the prerequisite conditions for work i . Equation (5) ensures that each task is assigned only to the required machine. Equation (6) imposes the

maximum maintenance time for the machine j for work i . Inequality (7) specifies the prerequisite conditions for machines. Equation (8) defines the production time of work i on machine j as the sum of the processing time per unit multiplied by the quantity of work i produced on the machine j , plus the machine setup time. Equation (9) ensures that production respects the machine's capacity. Equation (10) sets the start time of the first task or job i on machine j to 0. Equation (11) specifies that decision variables are binary. Finally, equation (12) ensures that the total maintenance period of each machine does not exceed the total available time (13). This constraint ensures that the energy usage and waste emissions of each machine do not exceed the total available operating time.

This study applied the Local Search Heuristic method to production planning, utilizing production data from a Made-to-Order and Make-to-Stock system of a company in Uttaradit Province. The study encoded the data in a numerical tabular format containing essential information about each machine's production process, task sequence, and the machine groups capable of handling production. The program then used machine-allocation switching principles to find the production pattern with the shortest overall production time. The results from each calculation cycle were recorded and compared. After a predetermined number of cycles, the program terminated and displayed the optimal solution, or Minimum Solution Value.

Results and Discussion

The research addressed two experimental objectives. The first aimed to determine the most appropriate production schedule by applying a mathematical programming model integrated with a local search heuristic, and the second aimed to improve the efficiency of production scheduling for an agricultural transport vehicle manufacturing company in Uttaradit Province by comparing the minimum makespan obtained from the mathematical model with that in the company's existing scheduling table. The study conducted each experiment on a computer equipped with a 3.0 GHz CPU, 16 GB of RAM, and 64-bit Windows 11.

The study collected all data directly from the factory. Due to the large number of products, the researcher categorized the scheduling problems into three sizes-small, medium, and large-to facilitate model testing. The study based the classification on the number of jobs and machines involved. The small-sized problem included the 50-mm booth set,

Gear Boost Set 203, and Front Beam Lock Pin. The medium-sized problem consisted of the chock bolt set and 25-mm bolts, while the large-sized problem encompassed all products combined. Table 5 presents the final production scheduling results for each problem size.

Table 5. Production scheduling problems of a case study of an agricultural transport vehicle manufacturing company in Uttaradit province

Problem Size	Product Items	No. of works (n)	No. of machines (m)
Small 1	50-mm booth set	6	7
Small 2	Gear Boost Set 203	6	7
Small 3	Front Beam Lock Pin	7	9
Small 4	25-mm bolts	15	9
Medium	50-mm booth set / 25-mm bolts	20	11
Large	All products	54	11

Scheduling program: The model was developed using the C++ programming language, which is a statically typed language, and incorporated a local search heuristic method (Frisch *et al.*, 2021; Chaouch *et al.*, 2021; Lu *et al.*, 2025) to randomly explore solutions for minimizing the makespan (Khamphrommi *et al.*, 2019; Fecarotti

et al., 2021; Wu *et al.*, 2021; Park *et al.*, 2025). The primary objective was to determine the optimal solutions across all problem sizes. A sample of the decision results for the production scheduling of the small-sized problem (Small 2) is presented in Table 6.

According to Table 6, the production scheduling involved seven machines and six work steps, where a value of 0 indicated that machine j did not process job i . After processing the data, the results showed that the maximum makespan among the seven machines was 6,961.23 minutes. The results also showed that specific machines, such as Machines 4 and 5, were used less frequently than others because they were designated for specific operations, including facing, turning, sharpening, and drilling.

Conclusions

Moreover, the developed program generated optimal production scheduling solutions that minimized the makespan across different problem sizes. Table 6 presents the analysis of the experimental results.

According to Table 7, the results demonstrated efficient utilization of all available resources. In the minor problem (Small 3), only one machine remained unused, resulting in a utilization rate of 88.89%, whereas all other cases achieved 100% utilization.

Table 6. Sample of Makespan of Front-Assembly Set

Order / Machine	m 1	m 2	m 3	m 4	m 5	m 6	m 7
n1	3122.19	0	1325.51	0	2125.34	0	515.25
n2	2518.51	0	1524.18	0	0	2856.72	2541.22
n3	0	1829.21	412.21	0	0	2125.21	1736.59
n4	0	720.21	547.23	0	0	156.17	
n5	0	0	451.54	236.51	0	726.44	446.57
n6	0	0	0	2546.12	156.21	754.69	1721.6
Total Makespan (minutes)	5640.7	2549.42	4260.67	2782.63	2281.55	6619.23	6961.23

Table 7. Conclusion of the minimum makespan of small-sized and medium-sized problems by using a mathematical programming model

Problems	Size (n × m)	Makespan (minutes)	Time for processing (seconds)	Unused machines (machines)	Percentage of machine used (%)	Total Carbon Footprint (CFP)
Small	6 × 7	7,547.34	0.125	0	100	112.96
Small 2	6 × 7	6,961.23	0.214	0	100	91.791
Small 3	7 × 9	5,015.42	0.115	1	88.89	157.36
Small 4	15 × 9	9684.42	0.354	0	100	215.23
Medium	20 × 11	1581.42	0.318	0	100	312.69

Therefore, optimizing the production scheduling for each problem enabled the efficient deployment of all machines in the factory. Previously, machine utilization relied primarily on the experience of operating workers, who often made unsystematic decisions without proper scheduling or planning. The experiment resulted in time losses due to setup and maintenance activities. The proposed production scheduling model improves production planning and maintenance coordination while minimizing machine downtime and breakdowns.

Result of improving efficiency: The primary objective of this research was to enhance production scheduling efficiency. The newly developed schedule was compared with the company's existing schedule, as shown in Table 8. The factory's production scheduling data indicated 50 workpieces, 10 machines, and several operational steps, which the study classified as a large-sized problem.

According to Table 8, the makespans for the previous and new production schedules were 38,561.12 minutes (approximately 81 days) and 27,421.18 minutes (approximately 57 days), respectively, assuming an eight-hour working day. The new production schedule, developed through the mathematical programming model, reduced the makespan by 11,139.94 minutes, or approximately 24 days, representing an efficiency improvement of 28.89%.

The major inefficiencies in the previous production scheduling stemmed from planning without accurate operational data from workers and unclear scheduling procedures, which led to improper task sequencing, unexpected costs, and unnecessary delays. These issues also caused delays in assessing the Carbon Footprint of Product (CFP). The previous production schedule generated a CFP of 1,387.79 kgCO₂e, whereas the new optimized schedule reduced it to 890.031 kgCO₂e, demonstrating a significant improvement in both scheduling efficiency and environmental performance.

To optimize the production scheduling of an agricultural transport vehicle manufacturing company in Uttaradit Province, this research aimed

to reduce operating times under actual factory regulations and constraints, following the company's experience with inefficiencies in production scheduling caused by limited machines and workforce. The study developed a mathematical programming model to minimize the makespan and supported it with a program that employs a local search heuristic to determine optimal solutions.

Operational time data from the first to the last process were collected

and used to construct the model. The data included product types, production order quantities, maintenance schedules, machine types and quantities, setup times, and production times for each process and product, along with relevant operational constraints. The problems were categorized into three sizes, small, medium, and large, based on the number of products and machines involved, with the large-sized problem encompassing all products and machines. The optimization of production scheduling was performed using the developed mathematical programming and local search heuristic method. The model developed in conjunction with heuristics programs was capable of accommodating changes in the production system, whether it was an increase in various machines due to expanded production capacity or a decrease in the machines due to sudden breakdowns or operational limitations. The research focused on developing a flexible system that could effectively adapt to changing production conditions.

The study collected operational time data from the first to the last process and used them to construct the model. The data included product types, production order quantities, maintenance schedules, machine types and quantities, setup times, and production times for each process and product, along with relevant operational constraints. The study categorized problems into small, medium, and large based on the number of products and machines involved, with the large category encompassing all products and machines. The study optimized production scheduling using the developed mathematical programming model and a local search heuristic. The model developed in conjunction with heuristics programs was capable of accommodating changes in the production system, whether it was an increase in various machines due

Table 8. Comparison results of makespan from previous and new production scheduling

Issues of comparison	Makespan of a large-sized problem (minutes)	Time Difference (minute)	Total Carbon Footprint (CFP) (kgCO ₂ e)	Percentage of efficiency improvement
Previous production scheduling	38,561.12		1,387.79	
New production scheduling	27,421.18	11,139.94	890.031	28.89 %

to expanded production capacity or a decrease in the machines due to sudden breakdowns or operational limitations. The research focused on developing a flexible system that could effectively adapt to changing production conditions.

The results revealed that the developed mathematical model successfully identified optimal production scheduling solutions across all problem sizes, enabling more efficient machine utilization for the large-sized problem, which represents the company's entire production scenario. The optimized schedule achieved a minimum makespan of 27,421.18 minutes, reducing production time by approximately 24 days (28.89%) compared with the previous schedule. In terms of environmental performance, the optimized schedule reduced the Carbon Footprint of Product (CFP) by 497.759 kgCO₂e, confirming that the research achieved its objectives in enhancing both production efficiency and environmental sustainability. The observed reduction in CFP of 497.759 kgCO₂e was not directly attributable to a decrease in energy consumption per unit; rather, it stemmed from enhancements in the overall efficiency of the production planning process. Optimizing production planning notably reduced the total makespan, idle time, setup time, and machine redundancy. Consequently, this optimization led to a decline in actual electricity consumption throughout the production process, despite the energy consumption per unit remaining unchanged. Thus, the overall reduction in the production system's total energy consumption drove the decrease in greenhouse gas emissions, rather than changes in energy consumption per unit. As a result, improvements in production planning led to a significant decline in total CFP, aligning with the calculated outcomes.

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Author Contributions

Chatchaphon Ketviriyakit: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Writing - Original Draft, Supervision, Project Administration, Funding Acquisition. Adul Phuk-in: Software, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision. All authors

have read and agreed to the published version of the manuscript.

Ethics Approval and Consent to Participate

The study entitled "*An Approach to Production Scheduling for Reducing Carbon Footprint in an Agricultural Transport Vehicle Manufacturing Company: A Case Study in Uttaradit Province*" did not require approval from a research ethics committee. This research focused exclusively on manufacturing processes and machinery operations within an industrial facility. Data collection involved measuring production processing times, electricity consumption, and waste generated during manufacturing processes.

The study did not involve human participants, human data, human biological materials, animals, or animal-derived data. Therefore, ethical approval and informed consent were not required in accordance with institutional and international research ethics guidelines.

Declaration of Generative AI

Generative Artificial Intelligence (Generative AI) was used in this study solely for language editing, grammar improvement, and enhancing the clarity and readability of the manuscript. The AI tool was not used for data collection, data analysis, interpretation of results, or the generation of scientific conclusions.

The authors carefully reviewed, verified, and revised all AI-assisted content included in the manuscript and take full responsibility for the accuracy, integrity, and final content of this research article.

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