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Simulation and Optimization of Production Scheduling in Multivariety Small-batch Mixed-flow Assembly Workshops Using IoT

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The mixed-flow production line has realized a production method featuring multiple varieties and small batches, retaining the advantages of large scale, high efficiency, and low cost of traditional assembly line production. The mixed-flow production line enhances production flexibility but also escalates the cost and demands of production management for the enterprise. To efficiently process a variety of products in small batches on the same assembly line, the issue of production sequencing for different products on the mixed-flow assembly line needs to be addressed. In this study, we utilize the FlexSim platform to simulate the workshop production activities of J Machinery Factory over one production cycle. By establishing a model and employing the OPTQUEST optimization module, the optimal solution is rapidly determined without increasing machine equipment, thereby maximizing total output profit. This provides a scientific quantitative basis for enterprise management and decision-making, ultimately enhancing competitiveness.

1. Introduction

The diversified market demands require manufacturing enterprises to shift from traditional mass production to a model of small batches with multiple varieties, catering to the dynamic changes and personalized needs of the market. Mixed-model assembly production represents a highly flexible manufacturing approach, where different types (or specifications) of products are continuously produced, often sharing similarities in operation and functionality but differing in model and specification. This approach effectively addresses the drawbacks of traditional single-variety mass production, avoiding the need for large inventories to respond to market demands. The production sequence in mixed-model assembly lines significantly affects production efficiency. The production sequencing problem in mixed-model assembly lines is a known

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nondeterministic polynomial-time hardness problem in combinatorial optimization.(1,2) A well-thought-out production sequence is of paramount importance for enhancing manufacturing efficiency, reducing various resource wastages, and enhancing a company's competitive advantage in the market economy. In response to the challenges posed by the diverse market demands, manufacturing enterprises have increasingly adopted mixed-model assembly production, which offers greater flexibility and responsiveness to changing market needs.

However, determining the optimal production sequence remains a critical challenge because of the complexity of the problem. Various factors such as production time, resource utilization, and minimizing changeover times need to be considered while optimizing the production sequence. Advanced optimization techniques, such as genetic algorithms or simulated annealing, are often employed to tackle this nondeterministic polynomial time-hard problem effectively. By addressing the production sequencing problem in mixed-model assembly lines, manufacturing enterprises can streamline their operations, reduce costs, and enhance their competitiveness in the market. Moreover, by aligning production sequences with market demands, companies can better meet customer expectations for customized and timely delivery, ultimately driving growth and profitability. The relationship between the FlexSim platform and IoT lies in their synergistic potential to achieve advanced simulation and control functionalities.(3–6) Their interplay encompasses several crucial aspects.

In this study, we improved the IoT sensor devices for gathering vast amounts of real-time data, including sensor readings and equipment statuses. FlexSim can leverage this data for simulation and analysis, enabling the evaluation of system performance, prediction of future behaviors, and optimization endeavors. Through the integration of data from the IoT sensor devices, FlexSim can dynamically access and employ real-world data for real-time simulation and control. This capability enables the investigated systems to adjust model parameters using real-time data, thereby achieving more accurate simulations of real-world scenarios and implementing real-time measures to enhance system performance. In the development process of IoT systems, FlexSim serves as a valuable tool for validating designs and control strategies. By simulating the behavior of IoT systems, it facilitates the assessment of the performance of products having variations in design, the identification of potential issues, and the subsequent improvements, thus saving time and resources. By combining the data from the IoT sensing devices with FlexSim's simulation capabilities, system optimization and future prediction become feasible. Through the analysis of historical and real-time data, opportunities for improvement can be identified, and future system behaviors can be predicted, enabling the formulation of more effective strategies.

The research on the production sequencing problem in mixed-model assembly lines started relatively late in China, and there are several main issues.

(a) Most studies have focused on either single-variety mass production or multivariety random production, with limited research on the common scenario of multivariety small-batch production sequencing encountered in practical production planning.
(b) Many small and medium-sized enterprises rely heavily on manual scheduling and allocation of workshop operations, which are often based on the experience of scheduling personnel.

In response to these issues, we take the production activities of a workshop within J Mechanical Factory as an example for one production cycle. It selects the total output profit as the production evaluation criterion, defined as the maximum value of [quantity of finished products × (selling price − cost) − fixed expenses]. In this study, we aim to address the production sequencing problem in J Mechanical Factory's mixed-model assembly line to determine the optimal production sequence to maximize total output profit. We utilize FlexSim simulation software to simulate the production activities of a workshop within J Mechanical Factory for one production cycle.(7) By establishing a simulation model, we can rapidly identify the optimal solution. FlexSim is chosen for its capability to model complex production processes and efficiently analyze various production scenarios, enabling the identification of the most profitable production sequence for the given production environment.

2. Methodology

The current commonly used research methods for the mixed-model assembly line production sequencing problem include traditional optimal solution algorithms,(8) artificial intelligence algorithms,(9) and computer simulation methods,(7) as depicted in Fig. 1. In recent studies, the integration of IoT sensors has gained attention, enhancing these methods by providing real-time data from the production line. These sensors allow for the collection of detailed information on equipment status, production progress, and environmental conditions, which can be fed into the algorithms and simulations. By incorporating IoT sensor data, we can improve the accuracy of production sequencing models, optimize real-time decision-making, and gain deeper insights into system performance, ultimately leading to more efficient and flexible assembly line operations. These methods encompass a range of approaches aimed at addressing the complexities of production sequencing in mixed-model assembly lines. Traditional optimal solution algorithms typically involve mathematical modeling and optimization techniques to find the most efficient production sequence, applying predefined criteria such as minimizing production time or resource utilization. On the other hand, AI algorithms, including genetic

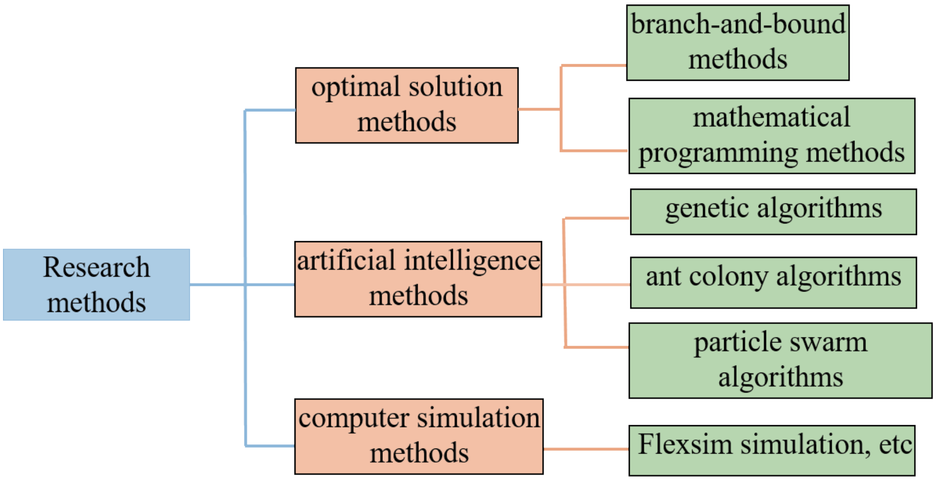


Fig. 1. (Color online) Classification of methods of solving production sequencing problems.

algorithms, simulated annealing, and neural networks, leverage advanced computational techniques to iteratively search for optimal or near-optimal solutions.

These algorithms can handle the combinatorial nature of the problem and adaptively adjust to changing production environments. Furthermore, computer simulation methods offer a practical approach to evaluate different production sequences in a virtual environment before implementation. By simulating the assembly line operations, these methods enable manufacturers to assess the performance of various sequencing strategies and identify potential bottlenecks or inefficiencies. The choice of method depends on factors such as the complexity of the production environment and the availability of data and computational resources. In practice, a combination of these methods may be employed to effectively tackle the mixed-model assembly line production sequencing problem and optimize production efficiency.

2.1 Analysis of characteristics and conditions of mixed-model production mode

The mixed-model assembly line is designed to meet the diverse and personalized market demands by assembling different products with similar basic features and assembly processes on the same assembly line interchangeably, instead of batch assembly in turn. This facilitates meeting the characteristics of diversified and personalized market demands. The design of mixed-model assembly lines generally should be based on the following conditions.

(a) Products have similar or identical structures and production processes.
(b) Rapid conversion times are ensured, while maintaining low conversion costs on the production line.
(c) The production management system strictly adheres to established procedures in formulating production plans.
(d) All stages of production are effectively coordinated and synchronized to minimize delays, reduce waste, and optimize workflow.
(e) Skilled and knowledgeable workers are employed to operate the production system efficiently.

These conditions ensure efficient and flexible production processes that can adapt to varying customer demands and market dynamics.

2.2 Analysis of issues to be addressed in mixed-model production lines

The first issue is balance, which involves task allocation that ensures workload balance at workstations. Line balancing is a medium- to long-term planning issue that involves factory construction, facility planning, and the allocation of equipment and personnel. Once established, it is generally not subject to short-term changes and is difficult to modify. The second issue is sequencing, which entails determining a good production sequencing scheme to improve production efficiency and respond quickly to market demands. Production sequencing is a short-term planning issue. Production decision-makers need to plan on a monthly, weekly, or even daily basis or on the basis of each batch order. Production sequencing affects the entire production process. According to Ref. 9, research objectives related to sequencing problems in mixed-model assembly lines are mainly focused on the following five aspects.

(a) Maintaining a constant utilization rate for each component on the assembly line.
(b) Balancing the workload (assembly time) at each workstation on the assembly line.
(c) Minimizing maximum delay time.
(d) Minimizing conveyor downtime.
(e) Maximizing the reduction of required equipment.

No matter which target is chosen as the research object, the ultimate goal that enterprises aim to achieve is consistent: to respond rapidly to market demand in order to maximize profits. In this paper, we focus on the mixed-flow assembly line sequencing problem at J Machinery Factory, under the premise that various costs have already been determined. The objective is to identify the corresponding production sequencing that maximizes the total output profit.

3. Workshop Production Planning Simulation Modeling

In this study, we aim to address the critical challenge faced by J Machinery Factory in optimizing their assembly line sequencing process. Despite having fixed costs, the dynamic nature of market demands necessitates a flexible and efficient production strategy. By examining the factors influencing production sequencing and analyzing their impact on overall profitability, we seek to provide actionable insights for J Machinery Factory to enhance its operational efficiency and competitiveness in the market. The significance of this research lies in its potential to offer practical solutions for real-world manufacturing scenarios. By optimizing assembly line sequencing, companies like J Machinery Factory can not only meet market demands promptly but also achieve maximum profitability. Our research will lead to a broader understanding of production management strategies, particularly in the context of responding to evolving market dynamics.

3.1 Analyses of production line at J Machinery Factory

FlexSim is a popular simulation software used for modeling, simulating, and analyzing complex systems in production, logistics, transportation, and more. It is primarily used to help businesses analyze processes, optimize resource allocation, and improve efficiency. When combined with the IoT systems, FlexSim models can significantly enhance their functionality and application potential. IoT systems refer to networks of devices, sensors, and other technologies that collect and communicate data. These devices provide real-time data that can be used to monitor and control actual systems, offering immediate feedback and supporting decision-making. In this study, we successfully integrated FlexSim models with IoT systems to achieve the following objectives.

(1) Real-time data-driven simulation: IoT systems provide real-time data such as machine status, equipment load, transport routes, and inventory levels. This data can be input into the FlexSim model, making the simulation results more accurate and reflective of real-world conditions. This enables businesses to analyze and optimize processes based on actual data.
(2) Remote monitoring and control: During production or logistics processes, IoT devices can monitor the operational status of machinery in real time. By connecting this data to the

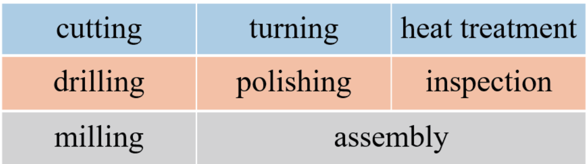
FlexSim model, immediate simulation analysis can be performed, helping managers make timely adjustments or predict potential issues.

(3) Enhanced decision support: With IoT data, FlexSim models can provide more dynamic and immediate suggestions, supporting more accurate decision-making. For example, in manufacturing, IoT system data allows FlexSim models to predict equipment failures, optimize production schedules, and manage inventory more effectively.

(4) Process optimization: IoT enables FlexSim models to simulate real-time operational conditions and quickly adjust various parameters within the model. This allows for testing different scenarios and achieving optimal resource allocation and process optimization.

(5) Predictive analytics and preventive maintenance: Using data obtained from IoT devices, FlexSim can perform predictive analysis, such as forecasting potential equipment failures and conducting preventive maintenance. This reduces downtime and enhances overall production efficiency. The layout of a workshop is shown in Fig. 2. In the next planning period, the factory will produce four products, each with nine orders. In the following discussion, one order is treated as one workpiece for simulation. The processing steps for each product are different, as Table 1 shows.

First, we select the maximum value of total output profit [number of finished products × (selling price − cost) − fixed expenses] as the production evaluation index. In actual production, if production tasks are not optimized through scheduling, the machining workshop will carry out production according to the sequence in which production tasks are received. We use FlexSim simulation software combined with the IoT systems to simulate the production activities of J Machinery Factory during one production planning period and determine the optimal production sequence for simulation experiments. For modeling convenience, we do not consider the last three identical processes for each product from heat treatment to assembly. The simplified processes include four steps: cutting (A), polishing (B), drilling (C), and milling (D), as shown in Fig. 3. The processing steps are A → B → A → D for Product 1, C → D → B → B for Product 2, A → D → B → C for Product 3, and A → B → B → C for Product 4. Summarizing the relevant information for these four products, we obtain the data in Table 2.



cutting	turning	heat treatment
drilling	polishing	inspection
milling	assembly	

Fig. 2. (Color online) Layout of J Machinery Factory's shop floor.

Table 1
Processing steps for products at J Machinery Factory.

Product No.	Processing steps
Product 1	cutting → polishing → cutting → milling → heat treatment → inspection → assembly
Product 2	drilling → milling → polishing → polishing → heat treatment → inspection → assembly
Product 3	cutting → milling → polishing → drilling → heat treatment → inspection → assembly
Product 4	cutting → polishing → polishing → drilling → heat treatment → inspection → assembly

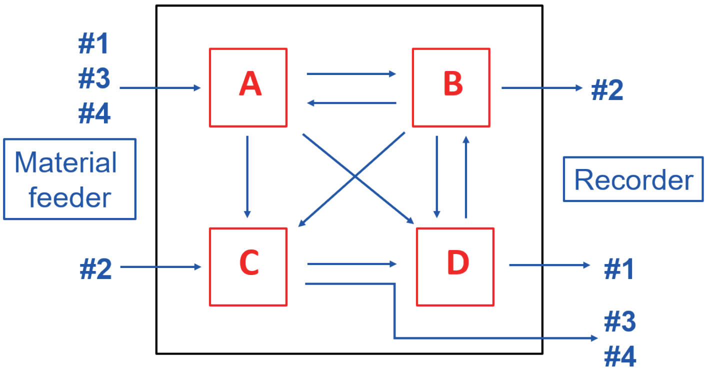


Fig. 3. (Color online) Simplified layout of J Machinery Factory.

Table 2
Summary of information for four products. WIP: work in progress.

Products	Selling price (unit: Yuan)	Material cost (unit: Yuan)	Order quantity	Manufacturing processes	Beginning WIP and current stage
#1	275	150	9	A→B→A→D	one item in front of machine B
#2	375	110	9	C→D→B→B	—
#3	240	90	9	A→D→B→C	one item in front of machine A
#4	305	95	9	A→B→B→C	one item in front of machine A

3.2 Simulation constraint analyses

The optimization objective of this study is to maximize profits without altering the existing production processes or increasing equipment and labor. Therefore, before modeling and simulating the production line of J Machinery Factory using Flexsim software, the following constraints need to be considered.

(1) Each work cycle spans 36 days, during which four different products are produced on the same production line.
(2) The four products on the production line share similar structures and processes but differ in model specifications.
(3) Production of the four products on the production line is mixed and continuous, rather than batchwise or sequentially.
(4) Each workstation has one machine, each with unique processing capabilities that cannot be exchanged or supported by others.
(5) The production rate for orders is continuous and fixed, with one order treated as one workpiece produced daily, and each workpiece requires one day of processing time at each workstation.
(6) Effects such as machine failures, worker breaks, and quality issues during production that may impact processing progress are ignored.

(7) Transition times on the production line are neglected.
(8) It is assumed that there is an adequate supply of components at each workstation, eliminating situations where production halts owing to material shortages.
(9) The total operating cost within one work cycle is $3000.

3.3 Workshop production planning simulation modeling

We utilize the simulation software Flexsim to model the production process in the machining workshop of J Machinery Factory, as illustrated in Fig. 4. The model mainly consists of generators, buffer zones, processors, and absorbers (represented by buffer zone 30). Generators create temporary entities, or production tasks, in accordance with a certain sequence or pattern. When new production tasks are added, the arrival frequency of the generators is refreshed. Generator 1 and Generator 170 respectively generate initial orders for work in progress. Generator 3 generates the remaining 33 orders, with different types of products represented by different colors. Additionally, a trigger is created in Generator 3 to set a label named “newlabel” with an initial value of 0. Buffer zones serve as temporary storage for work in progress. Given the limited area and capacity of the actual workshop, the maximum capacity of all buffer zones in this model is set to 36. Subsequently, a global table named processTable1 is established to read the value of “newlabel” in the entity flow direction of buffer zone 8 and point to the columns of processTable1, enabling the implementation of different manufacturing processes for various products. Processors are the primary entities in the model responsible for processing and manufacturing products. Within each processor, departure triggers are set to increment the value of the “newlabel” label by 1.

A higher label value indicates that the order is in a later stage of production and is approaching completion faster. This setup facilitates the flow of entities in buffer zone 8. Absorbers handle the entry of finished products into inventory. In addition, five tables, namely ProcessTable1,

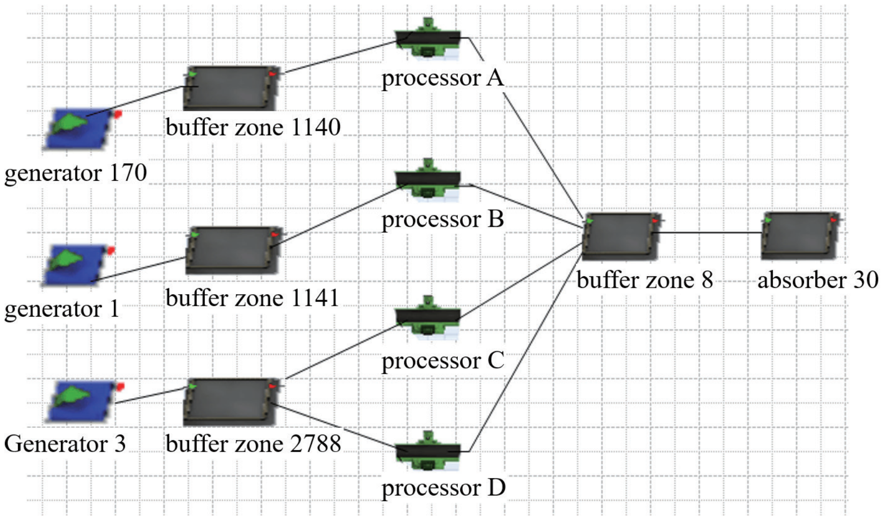


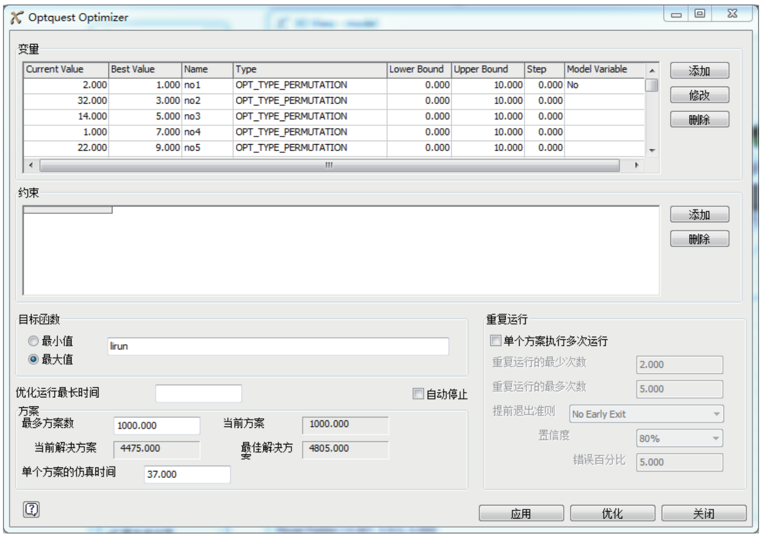
Fig. 4. (Color online) Simulation model of the production line at J Machinery Factory.

OrderTable, Shuliang, Lirun, and Ziliao, are added under the global table. ProcessTable1 is utilized to regulate the entity flow in buffer zone 8, while OrderTable displays the production sequence. Shuliang's first column records the number of orders placed, and the second column records the number of products produced, both automatically filled in by the program. This is achieved through programming in the departure triggers of buffer zone 2788 and the entry triggers of buffer zone 30. Lirun displays the total profit generated, calculated as [number of finished products × (selling price − cost)]. Ziliao includes information on product selling prices and costs. Finally, in the OPTQUEST window, the types of decision variables are defined, variable associations are established, and the objective function for optimization is determined.

4. Simulation Model Operation and Results Analyses

To maximize the profit of production output within a planning period, J Machinery Factory needs to conduct optimization using the OPTQUEST module in Flexsim software. The decision variables to be set include the sequence of product production and the output profit. Initially, sequential decision variables are added through OPTQUEST. As the next planning period requires the production of 33 new products, 33 sequential decision variables need to be added, defined as no1 to no33, and linked to corresponding rows in the order table. Furthermore, another variable, named completequantity, is added to the OPTQUEST decision variable table to reflect the total output quantity of products. Lastly, another variable named lirun is added to the OPTQUEST decision variable table, also establishing associations, to calculate the total profit of production within a planning period. This variable is then used in the objective function of OPTQUEST, which is defined as max(lirun).

The basic design of the objective model and the definition of decision variables aimed at maximizing output profit have been completed as depicted in Fig. 5. Through multiple iterations



Current Value	Best Value	Name	Type	Lower Bound	Upper Bound	Step	Model Variable
2.000	1.000	no1	OPT_TYPE_PERMUTATION	0.000	10.000	0.000	No
32.000	3.000	no2	OPT_TYPE_PERMUTATION	0.000	10.000	0.000	
14.000	5.000	no3	OPT_TYPE_PERMUTATION	0.000	10.000	0.000	
1.000	7.000	no4	OPT_TYPE_PERMUTATION	0.000	10.000	0.000	
22.000	9.000	no5	OPT_TYPE_PERMUTATION	0.000	10.000	0.000	

○ 最小值
● 最大值
lirun

优化运行最长时间
☐ 自动停止

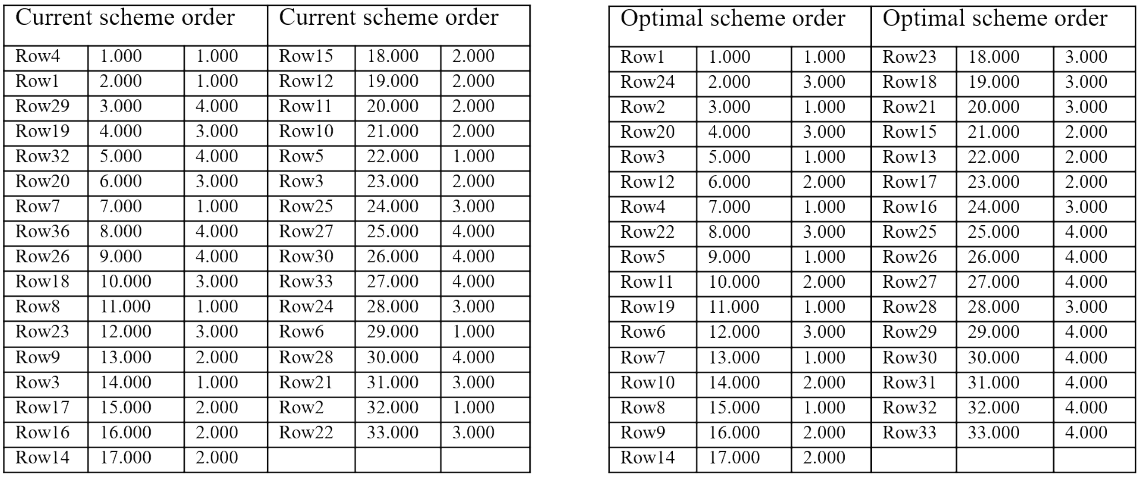
最多方案数 1000.000
当前方案 1000.000
当前解决方案 4475.000
最佳解决方案 4805.000
单个方案的仿真时间 37.000

☐ 单个方案执行多次运行
重复运行的最少次数 2.000
重复运行的最多次数 5.000
提前退出准则 No Early Exit
置信度 80%
错误百分比 5.000

Fig. 5. (Color online) Optimization data output of the simulation results.

and experiments, it has been observed from the data that when Generator 3 generates a temporary entity count of 25, production should cease, resulting in a greater profit compared with producing all 36 orders. Therefore, the temporary entity input to Generator 3 is halted when the count reaches 25, indicating the completion of 28 orders. The model is set to run a maximum of 1000 scenarios. After running the model multiple times, the simulation optimization results are shown in Fig. 5. Upon completion of the model run, the corresponding production sequence is written into the global table "order table", the data of which are given in Figs. 6(a) and 6(b). This analysis highlights the importance of strategically managing the production process to maximize profitability. By optimizing the production sequence and output quantities, significant improvements in overall profit margins can be achieved. Furthermore, the iterative nature of the experimentation process underscores the dynamic nature of production optimization and the need for ongoing refinement and adjustment to achieve optimal results.

The current solution refers to the scenario obtained after running the model for the 1000th time, while the optimal solution is derived through optimization using the OPTQUEST module. As depicted in Fig. 6, the current production scheme is as follows: #1→#1→#4→#3→#4→#3→#1→#4→#4→#3→#1→#3→#2→#1→#2→#2→#2→#2→#2→#2→#2→#1→#2→#3→#4. On the other hand, the optimal production scheme is #1→#3→#1→#3→#1→#2→#1→#3→#1→#2→#1→#3→#1→#2→#1→#2→#2→#3→#3→#3→#2→#2→#2→#2→#3. By comparing the profit values between the "current solution" and the "optimal solution", it is evident that optimization indeed leads to an increase in total output profit. According to Fig. 5, the net profit for the current scheme is 4475−3000=1475, whereas the net profit for the optimal solution is 4805−3000=1805. This indicates that the optimal solution generates an additional profit of 430 compared with the current scheme, resulting in a profit increase of 27.32%. Therefore, modeling and simulating production activities for J Machinery Factory using the FlexSim platform have yielded desirable results, providing the factory's material handlers with effective production sequencing schemes capable of significantly increasing revenue.



Current scheme order			Current scheme order		
Row4	1.000	1.000	Row15	18.000	2.000
Row1	2.000	1.000	Row12	19.000	2.000
Row29	3.000	4.000	Row11	20.000	2.000
Row19	4.000	3.000	Row10	21.000	2.000
Row32	5.000	4.000	Row5	22.000	1.000
Row20	6.000	3.000	Row3	23.000	2.000
Row7	7.000	1.000	Row25	24.000	3.000
Row36	8.000	4.000	Row27	25.000	4.000
Row26	9.000	4.000	Row30	26.000	4.000
Row18	10.000	3.000	Row33	27.000	4.000
Row8	11.000	1.000	Row24	28.000	3.000
Row23	12.000	3.000	Row6	29.000	1.000
Row9	13.000	2.000	Row28	30.000	4.000
Row3	14.000	1.000	Row21	31.000	3.000
Row17	15.000	2.000	Row2	32.000	1.000
Row16	16.000	2.000	Row22	33.000	3.000
Row14	17.000	2.000			

(a)

Optimal scheme order			Optimal scheme order		
Row1	1.000	1.000	Row23	18.000	3.000
Row24	2.000	3.000	Row18	19.000	3.000
Row2	3.000	1.000	Row21	20.000	3.000
Row20	4.000	3.000	Row15	21.000	2.000
Row3	5.000	1.000	Row13	22.000	2.000
Row12	6.000	2.000	Row17	23.000	2.000
Row4	7.000	1.000	Row16	24.000	3.000
Row22	8.000	3.000	Row25	25.000	4.000
Row5	9.000	1.000	Row26	26.000	4.000
Row11	10.000	2.000	Row27	27.000	4.000
Row19	11.000	1.000	Row28	28.000	3.000
Row6	12.000	3.000	Row29	29.000	4.000
Row7	13.000	1.000	Row30	30.000	4.000
Row10	14.000	2.000	Row31	31.000	4.000
Row8	15.000	1.000	Row32	32.000	4.000
Row9	16.000	2.000	Row33	33.000	4.000
Row14	17.000	2.000			

(b)

Fig. 6. (a) Current scheme order and (b) optimal scheme order.

5. Conclusions

In this paper, we addressed the problem of production scheduling for a mixed-flow assembly workshop with multiple product varieties and small batch sizes, utilizing computer simulation methods. Initially, a production planning model for one cycle of operations in the machining workshop (referred to as J) was established using the FlexSim platform. Subsequently, based on the existing production tasks and equipment within this workshop, and without altering the original production process or increasing equipment or labor, the OPTQUEST optimization module was employed to rapidly determine the optimal solution, aiming to maximize the overall output profit. A comparison between the “current solution” and the “optimal solution” in terms of profit values clearly demonstrated that the optimized product scheduling method indeed enhanced the overall output profit. Compared with traditional optimal solution algorithms and artificial intelligence algorithms, employing computer simulation methods to address the production scheduling problem for different products on a mixed-flow assembly line offered advantages such as lower computational complexity, visualization-based implementation, high efficiency, and global optimization capabilities. Therefore, employing computer simulation methods for workshop production scheduling optimization not only provided effective production scheduling solutions to increase revenue for the factory’s material feeders but also facilitated the provision of scientific and quantitative foundations for decision-making by senior management, thereby achieving the optimal core objectives of workshop production planning: maximizing overall output profit and enhancing the company’s competitiveness.

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