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OPTIMIZATION OF MULTI-STAGE PRODUCTION SCHEDULING OF AUTOMATED PRODUCTION

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Abstract
With the continuous growth of the automation level, the production process is featured by multiple stages and process parameters. There is a huge sum of diverse data on automated production. With a low value density, these data come from heterogenous sources, and respond to lots of concurrent processing demands. It is necessary to simulate and optimize the production scheduling of the automated production system. Drawing on the existing research, this paper illustrates the process of multi-stage production scheduling of automated production, and simulates the automated production line on Plant Simulation. The flow of the simulation model was illustrated, the simulation objectives were specified, and the model hypotheses were detailed. From the angle of deterministic simulation modelling, a joint optimization model was established for the multi-stage production scheduling of automated production, and the production task assignment was improved for traditional pull scheduling model to meet the demand of dynamic collaborative demand for machines. The proposed model was proved effective through simulations.
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Key Words: Automated Production, Multi-Stage Production, Production Scheduling

1. INTRODUCTION

Manufacturing strategies like Made in China 2025 and Industry 4.0 promote the development of automated production technologies [1-5]. Modern production fully integrates new generation information technologies (IT), such as the Internet of things (IoT), the big data, and cloud computing, and realizes high connectivity, perception, precision, and automation level [6-11]. Currently, production is shifting from largescale repetitive manufacturing to small-batch non-repetitive manufacturing. The production scheduling of the automated production system has become a hot topic in the field of modern production [12-17]. With the continuous growth of the automation level, consumers raise higher demand for personalized and customized products. The production process is now featured by multiple stages and process parameters. There is a huge sum of diverse data on automated production. With a low value density, these data come from heterogeneous sources, and respond to lots of concurrent processing demands. This brings a huge challenge to multi-stage production scheduling.

Some job-shops require refined production scheduling, which needs to grasp the real-time processing state of each part. However, the existing scheduling plans cannot fully satisfy the scheduling needs of enterprises. To understand the processing state of each part, Zhou et al. [18] proposed online job-shop scheduling based on single part management, and combined field computer terminals with management computer terminals for simulation analysis. To better respond to diverse consumer needs, Liu et al. [19] probed deep into theories and actual models of corporate production management, and realized a production scheduling system based on process route optimization. The system balances the capacity of main machines on the process route, and thereby adapts to the new economic environment of the steel industry. Gamage and de Silva [20] adopted genetic algorithm (GA) to schedule and manage tasks in an environment where multiple operations compete for limited resources. To achieve system objectives, the resources were planned, assigned, and rearranged, in the case of performance decline and machine failure. In this way, the production system could adapt to the high-priority operations, which may be introduced after initial scheduling. Finally, their algorithm was proved effective through simulation.

To deliver the materials according to the agreed schedule, it is a must to make a good plan for the industrial production of many components. During the production, some problems may arise that delay the planned work. Most managers resort to deterministic methods to prepare the production schedule, without considering the probability of the said problems. Sbragio and Do Amaral [21] employed Monte-Carlo technique to simulate the production schedule of 350 welded parts, and determined the contract delivery date of the parts under a certain confidence. Tsukanov and Kovrizhnykh [22] analysed the factors bring the necessity of production schedule adjustment, and evaluated their impacts on the schedule execution. In addition, the stability related to plan preparation and adjustment was discussed, and the proposed method was realized by neural network (NN) and GA. Tsukanov and Kovrizhnykh also demonstrated through simulation that their method enhanced the stability of the production schedule against changes, and improved the productivity and lowered the cost of complex structured production.

From various angles, the above studies on multi-stage production scheduling yield effective solutions to problems on different levels. However, most of them rely on static management, and rarely consider collaborative production scheduling (CPS) or assign production tasks in the light of CPS. Therefore, this paper simulates the multi-stage production scheduling optimization of automated production. Drawing on the existing research, Section 2 illustrates the simulation problem of multi-stage production scheduling of automated production, simulates the automated production line on Plant Simulation, provides the flow chart of the simulation model and the objectives of simulation, and details the hypotheses of the simulation model. From the angle of deterministic simulation modelling, Section 3 establishes a joint optimization model for the multi-stage production scheduling of automated production. Section 4 improves the production task assignment for traditional pull scheduling model, such as to meet the dynamic collaborative demand for machines. The proposed model was proved effective through simulations.

2. SIMULATION PROBLEM DESCRIPTION

Drawing on the previous research, this paper establishes a joint optimization model for the multi-stage production scheduling of automated production, from the angle of deterministic modelling. So far, no scholar has included preventive maintenance of automation machine into production scheduling. To make up for the gap, this paper fully considers the effect of machine load, the nonlinear relationship between machine load and early delivery period, and the interplay between preventive machine maintenance and production scheduling, before setting up a production scheduling optimization model for the multi-stage simulation model of the automated production system.

Multi-stage automated production systems are usually very complex. Suppose the multi-stage simulation model of the automated production system needs to process H types of products, and its production cycle contains T stages of equal length. It is assumed that all processing parameters are known prior to every new production cycle; the manufacturer starts production after receiving an order from consumers, and completes delivery before the end of the delivery period agreed by the consumers. Let c_{ht} be the demand for product g before the end of each production cycle. As long as the product supply-demand relationship remains certain, any form of shortage will bring a penalty cost to the manufacturer, and any surplus products must be stored until an order for such products appear again, causing an inventory cost.

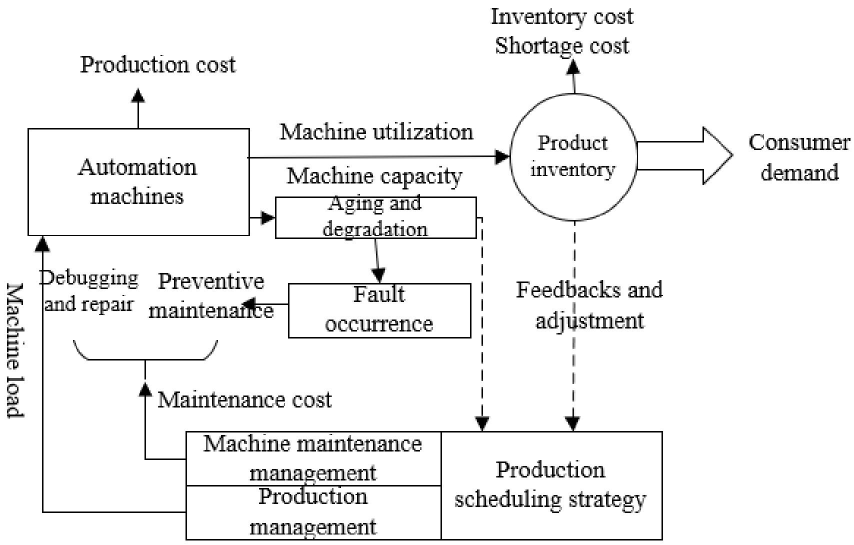

Figure 1: Production scheduling process.

The automated production system involves multiple production stages. It is necessary to specify the operations in each stage. Fig. 1 shows the production scheduling process of the multi-stage automated production system. Let $K_h = \{k:n\}$ be the set of operations to be executed to manufacture product g. Then, different operations can be processed on the same automation machine in different stages. The automated production system contains N automation machines, each of which has a limited capacity.

This paper simulates the automated production line on Plant Simulation. With the aid of computer simulation technology, the production progress of an actual job-shop was simulated, and used to optimize the automated production line, making it more in line with consumer demand for products. Plant Simulation offers a large quantity of object libraries related to production, including material library, transport library, information library, and statistical library, as well as various auxiliary tools. Before modelling the production line, it is necessary to select modelling objects, and describe them and their functions. Table I lists some of the objects of our simulation model for the automated production line.

The simulation model established on Plant Simulation is graphical and multi-layered. Through the setting of model parameters and SimTalk programming, the simulation process of the automated production line can be controlled in a refined manner, making modelling easier and more flexible. Fig. 2 shows the flow of the simulation model after the production scheduling in Fig. 1. The types of output products vary with the contents of processing operations.

Table I: Some objects of our simulation model.

Simulation model objects	***Source***	***Drain***	***SinglePro***	***Connector***	***Buffer***
Simulation system objects	Raw material library	Finished product library	Workstation	Route	Buffer zone
Functions	Source of raw materials	Storage of processed products	Processing machines	Logistics machines	Waiting zone of workstations
Simulation model objects	*EventController*	*BottleneckAnalyzer*	*Chart*	*Method*	*ShiftCalendar*
Simulation system objects	Working time	Machine utilization	Figures and tables	Issuance method	Batch log
Functions	Simulation event control	Bottleneck analysis	Figure and table analysis	Simulation process control	Setting production scheduling plan

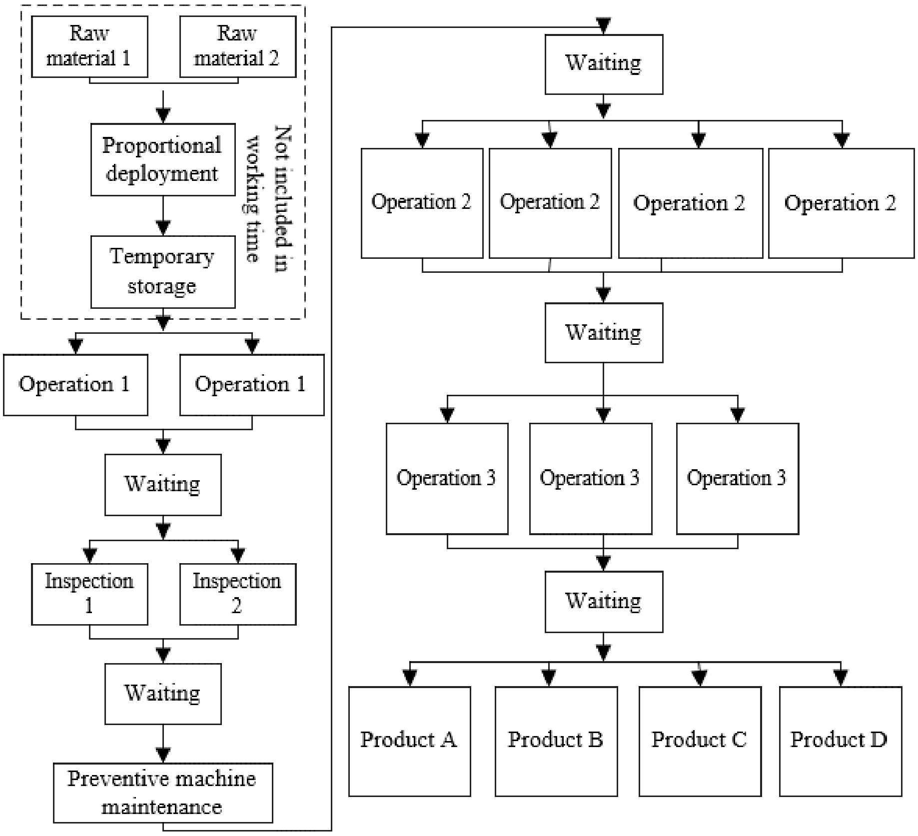

Figure 2: Flow of simulation model.

The simulation objectives of the proposed automated production line are as follows:

(1) According to the processing techniques, the processing time of each operation, and the actual situation of the job-shop, build a production line model on Plant Simulation, and input the relevant parameters. Analyse the machine operation data to find out the bottlenecking operations of the production line.

(2) Design multi-stage simulation experiments for the bottlenecking operations. Identify the leading impactors of these operations by changing each possible factor in turn, including machine utilization, production pace, etc. On this basis, optimize the automated production line, so that the production efficiency can meet the product needs of consumers.

(3) Verify the effectiveness of the optimization by comparing the machine operating states before and after the optimization.

To facilitate data collection and analysis during the simulation, the proposed simulation model must satisfy the following requirements:

(1) The simulation model can reflect the production situation of the production line in actual processing.

(2) The machine positions in the simulation model are the same as the actual positions.

(3) The processing time of the simulation model equals the actual production time.

The proposed optimization model was developed under the following hypotheses:

(a) Each of the N automation machines in the simulation model may fail, and the failure processes are independent of each other.

(b) The automation machines in the simulation model may age and degrade. The aging and degradation processes can be characterized by random Weibull distribution with two parameters.

(c) Once it fails, an automation machine in the simulation model needs to be debugged and repaired to eliminate the failure. The simple debugging and repair only restore the production function of the machine, without changing the aging and degradation degree.

(d) All the automation machines in the simulation model need non-regular preventive maintenance. During the preventive maintenance, each machine is fully recovered through debugging, overhaul, and part replacement, and the aging and degradation degree is reset to zero. That is, after preventive maintenance, the N automation machines in the system will have the same life and failure rate functions. In the absence of preventive maintenance, the aging and degradation degree will be positively proportional to the continuous processing time. This paper divides the entire production cycle into P stages of equal length. The preventive maintenance can be implemented in the early stage of the production cycle. Since the interval between two continuous preventive maintenance operations varies with machines, the following preventive maintenance strategy is preferred:

(1) It is assumed that the maintenance cost of a failed machine in the simulation model linearly increases with the interval between the current and previous maintenance operations.

(2) It is assumed that the preventive maintenance in the simulation model requires the same time on the N automation machines.

(3) It is assumed that the consumer demand reflected in product orders is known.

Given the influence of the known consumer demand, processing parameters, machine failure features on the preventive maintenance strategy, as well as the influence of simple debugging and repair on machine function and capacity, this paper defines the objectives of production scheduling optimization of the simulation model: minimizing the material cost, inventory cost, preventive maintenance cost, and machine maintenance cost, and minimizing the probability of shortage, by improving the strategies for material deployment and preventive machine maintenance for each product in each stage of each production cycle.

3. MODELLING AND TASK ASSIGNMENT

Let PTD and PND be the production cost and machine maintenance cost of the automated production simulation model, respectively. Then, the objective function of the joint optimization model for multi-stage production scheduling can be expressed as:

$$PD = Min\left(PTD + PND\right) \tag{1}$$

The set of H products is denoted as $h = 1, 2, ..., H$; the set of N machines is denoted as $n = 1, 2, ..., N$; the set of T production cycles is denoted as $t = 1, 2, ..., T$; the set of K_h operations of product h is denoted as $k = 1, 2, ..., K_h$; the number of work-in-progress (WIP) parts of product h on operation k in production cycle t is denoted as Q_{htk}; the inventory cost per unit of WIP parts of product h on operation k in production cycle t is denoted as θ_{htk}; the inventory of product h at the end of production cycle t is denoted as SE_{ht}; the unit inventory cost of product h in production cycle t is denoted as f_{ht}; the shortage penalty cost of product h in production cycle t is denoted as y_{ht}; the shortage of product h at the end of production cycle t is denoted as Y_{ht}. Then, the production cost of the automated production simulation model can be calculated by:

$$PTD = \sum_{h=1}^{H}\sum_{t=1}^{T}\theta_{ht}Q_{ht} + \sum_{h=1}^{H}\sum_{t=1}^{T}\left(f_{ht}SE_{ht} + y_{ht}Y_{ht}\right) \tag{2}$$

Let r_u and r_o be the unit cost of preventive maintenance, and simple debugging and repair, respectively; M_t be the expected number of failures of a machine in production cycle t; C_t be a decision variable reflecting whether a machine receives preventive maintenance (if yes, $C_t = 1$; otherwise, $C_t = 0$). The machine maintenance cost can be calculated by:

$$PND = \sum_{t=1}^{T}\left(r_u C_t + r_o M_t\right) \tag{3}$$

Eq. (3) shows the machine maintenance cost covers preventive maintenance cost, and the debugging and repair cost.

Let $SE_{h,t\text{-}1}$ and $Y_{h,t\text{-}1}$ be the inventory and shortage of product h at the end of the previous production cycle t-1, respectively; A_{ht} and c_{ht} be the production and demand of product h in production cycle h, respectively. During production scheduling, the balance of product inventory in each production cycle can be expressed as:

$$SE_{h,t-1} + A_{ht} + Y_{ht} + Y_{h,t-1} - SE_{ht} = c_{ht}, \forall h,t; \tag{4}$$

Let $Q_{h,t\text{-}1,k}$ be the number of WIP parts of product h on operation k in the previous production cycle t-1; A_{htk} and S_{htk} be the production and material input of product h on operation k in production cycle t, respectively. During each production cycle, the balance of WIP parts can be expressed as:

$$Q_{hok} = Q_{h,t-1,k} - A_{htk} + S_{htk}, \forall h,t,k; \tag{5}$$

The machine capacity constraints are given in Eqs. (6) and (7). Let $G^0{}_t$ be the rated capacity of a machine in production cycle t; w_u and w_o be the unit time of preventive maintenance, and simple debugging and repair, respectively. Then, we have:

$$\sum_{h=1}^{H} A_{ht} \le G_t^0 - w_u C_t - w_o M_t, \forall t; \tag{6}$$

Eq. (6) shows that the actual capacity of a machine is smaller than the rated capacity minus the time of preventive maintenance and the time of simple debugging and repair.

Let XS be the stepwise linear regression of a non-fixed early delivery period function. Under the situation of XS, the machine load is divided into i parts; the expected number of machine failures in production cycle t is divided into j parts. Let β_{ij}, b_{ij}, and d_{ij} be the regression coefficient of machine load, the intercept, and the regression coefficient of M_t, under the situation of XS, respectively. Then, the machine capacity must satisfy the constraint of the non-fixed early delivery period function:

$$\sum_{h=1}^{H} A_{htk} \le \beta_{ij} \sum_{h=1}^{H} Q_{htk} + b_{ij} + d_{ij} M_t, \forall t,k \tag{7}$$

Let s_v be the machine failure rate function; $x^Y{}_t$ and $x^O{}_t$ be the aging and degradation degrees of a machine at the early stage and late stage of production cycle t, respectively; l_{ht} and S_{ht} be the production time and material input of product h in production cycle t, respectively. The other constraints are given in Eq. (8), including the expression of the expected number of machine failures, the relationship between the aging and degradation degrees at the early stage and late stage of the production cycle, the relationship between the aging and degradation degree at the early stage of the current production cycle, and that at the late stage of the previous production cycle, as well as the nonnegative constraint of each decision variable.

$$\begin{cases} M_t = \int_{x_t^Y}^{x_t^O} s(v)dv, \forall t; \\ x_t^O = x_t^Y + \sum_{h=1}^{H} \sum_{k=1}^{K_h} l_{ht} A_{htk}, \forall t; \\ x_t^Y = x_{t-1}^O (1 - C_t), \forall t; \\ Q_{htk}, SE_{ht}, Y_{ht}, A_{ht}, S_{ht}, C_t \ge 0, \forall h,t,k \end{cases} \tag{8}$$

The traditional pull and push production scheduling systems face many limitations in automated job-shops with a multi-stage simulation model of the automated production system, and a relatively complex production environment. Considering the actual production scheduling needs, this paper improves the traditional pull production scheduling control model. As the bottom layer of machine load control, production task assignment follows certain control rules to assign different processing priority to the tasks being handled in the production task execution center (PTEC). The idle machines in the PTEC will choose to process the top priority task. In this paper, the tasks are assigned based on the improved operation delivery period priority rule (ODPPR).

Suppose the task for a product contains l operations. Let PH_j be the delivery period of task j; EPH_j^l be the delivery period of operation l of task j. Then, the delivery period of the last operation of task j is the delivery period of the product. The delivery period of operation l of task j can be characterized by $XQPP_j$:

$$EPH_j^l = PH_j - \sum_{m=l+1}^{L} XQPP_j^m, l \in \{1,2 \ldots L-1\} \tag{9}$$

Let p_N be the current production stage; OST_j be the task assignment time. Then, the improved ODPPR can be expressed as:

$$EPH_j^l = p_N + \frac{\sum_{m=1}^{l} XQPP_j^l}{\sum_{m=1}^{L} XQPP_j^m} * (PH_j - p_N), p_N < PH_j \tag{10}$$

If p_N is greater than or equal to PH_j, EPH_j^l equals OST_j.

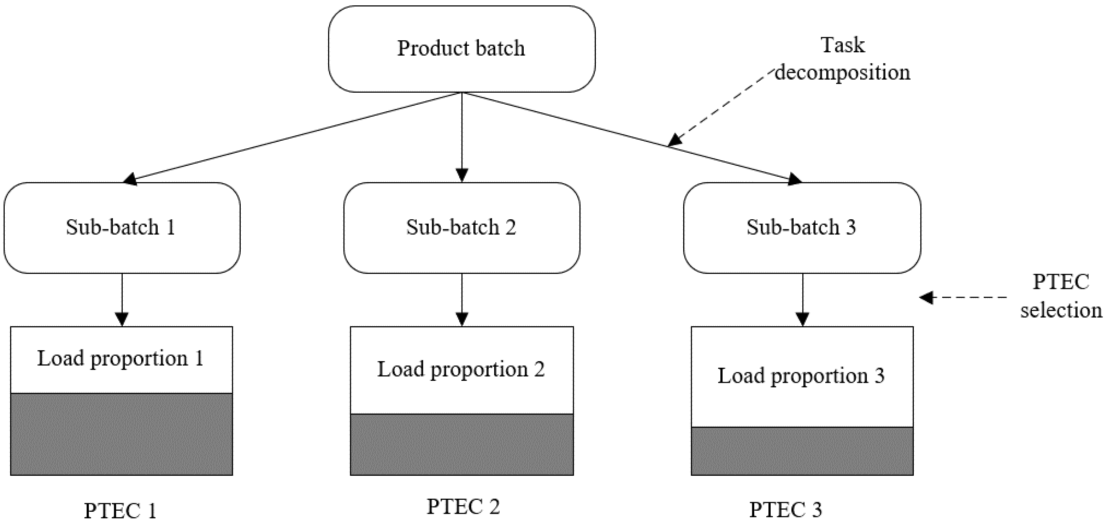

Figure 3: Task decomposition and PTEC selection.

In the automated production simulation model, the product being ordered often requires many associated tasks. Any tardiness in any task or operation may delay the delivery of the product. To realize the dynamic collaboration between associated tasks, it is important to adjust the priority of these tasks in real time, with the progression of the production. Otherwise, the associated tasks of the product cannot be completed in sync.

Fig. 3 illustrates task decomposition and PTEC selection. Let OST_j be the assignment time of task j. Eqs. (11) and (12) show the task assignment rules following the improved ODPPR. When the tasks are assigned at time p_N of the current production stage, it is necessary to compute the delivery period of each operation of each task:

$$EPH_j^l = p_N + \frac{\sum_{m=1}^{l} XQPP_j^l}{\sum_{m=1}^{L_j} XQPP_j^m} * (DPP - p_N), p_N < DPP \tag{11}$$

Based on the PTEC sequencing rule, the top priority task is selected for execution. Before execution, it is necessary to check the collaboration time of associated tasks, and update the task sequence. If p_N is greater than or equal to PH_j, EPH_j^l equals OST_j. Let D be the number of product batches. For the products in batch D, the delivery period of task j is characterized by $XQPP_{Dj}$, i.e., the total number L_j of operations of task j; the total number of operations in the tasks for the products in batch D is denoted as L_D, and their delivery period as PH_t. Then, the assignment time OST_j of task j can be calculated by:

$$OST_j = PH_t - \left(\sum_{n=1}^{L_D} XQPP_{D_j}^n + \sum_{m=l}^{L_j} XQPP_j^m \right) \tag{12}$$

4. SIMULATION AND RESULTS ANALYSIS

To verify its feasibility, the proposed production scheduling strategy was verified through the simulation of the actual production of the products in batch D from a Chinese enterprise. Two products h1 and h2 were selected from that batch. The former is composed of parts A and B, and the latter of parts C and D. Table II shows the delivery period and batch information of the two products.

Table II: Delivery period and batch information of the two products.

Products		***h*1**		***h*2**	
Batch size		100		200	
Mean delivery period of parts		0.8		0.5	
Parts		A	B	C	D
Batch size		100	100	200	200
Mean delivery period of each part	Operation 1	1.2	0.2	0.8	0.6
	Operation 2	1.6	0.9	1.2	0.4
	Operation 3	1.7	1.3	0.7	1.1
Planned assembly time		55			

Table III lists the optimal solutions to simulation parameters for different production cycles. The optimal total production cost was 5,576,489, which corresponds to the series of non-regular preventive machine maintenance (0, 0, 1, 0, 0, 1, 0, 1). The eight production cycles being selected contain 300 sub-problems to be solved. Suppose it takes 4 s to solve each sub-problem. Then, 14.87 min is necessary to solve the sub-problems step by step. Since our production scheduling strategy adopts the PTEC sequencing rule, the total solving time was 7.954 min under the framework of dynamic CPS. The solving time was much shorter than that of the stepwise strategy.

Table III: Optimal solutions to simulation parameters for different production cycles.

	A_1	A_2	Q_1	Q_2	S_1	S_2	SE_1	SE_2
t1	1325	1037	11248	10251	13262	15162	2	5
t2	1318	1185	10952	11627	1284	1425	1	3
t3	1074	1279	11328	10748	1108	1362	2	5
t4	1526	1382	12047	11508	1362	1418	0	2
t5	1375	1625	10952	11326	1457	1294	1	3
t6	1288	1329	10127	11062	1305	1472	0	2
t7	1428	1608	10716	11326	1527	1362	1	1362
t8	1524	1057	11047	10738	1426	1274	1085	1

Tables IV and V present the simulation outputs of processors, and the statistics on the parameters of the simulation cases, respectively.

This paper counts the production costs of all simulation cases. Fig. 4 plots the distribution of calculated production costs. The preventive maintenance sequence corresponding to the optimal solution was (0, 0, 1, 0, 1, 1, 0, 1). In this case, the production cost was 5,576,489. If preventive machine maintenance is arranged in each cycle, the corresponding sequence and production cost were (1, 1, 1, 1, 1, 1, 1, 1) and 5,624,896, respectively. In this case, the machine maintenance cost increased. If no preventive machine maintenance is arranged in each cycle, the corresponding sequence and production cost were (0, 0, 0, 0, 0, 0, 0, 0) and 5,688,562, respectively. In this case, the maintenance cost increased, owing to machine aging or degradation. Therefore, the optimal strategy is neither arranging preventive maintenance in each cycle, nor not doing so. The optimal scheduling effect can be achieved by striking a balance between production scheduling and decision-making of preventive maintenance.

Table IV: Simulation outputs of processors.

Object	**1**	**2**	**3**	**4**	**5**	**6**
Class	*Processor*	*Processor*	*Processor*	*Processor*	*Processor*	*Processor*
Processing	75.48 %	74.15 %	47.26 %	45.35 %	81.75 %	23.58 %
Setup	24.15 %	22.52 %	29.37 %	28.49 %	15.42 %	11.72 %
Idle	0.24 %	0.26 %	22.15 %	24.53 %	0.45 %	65.15 %
Block	0.01 %	0.00 %	0.02 %	0.01 %	0.00 %	0.00 %
Object	**7**	**8**	**9**	**10**	**11**	**12**
Class	*Processor*	*Processor*	*Processor*	*Processor*	*Processor*	*Processor*
Processing	26.42 %	22.18 %	27.46 %	25.17 %	29.48 %	27.53 %
Setup	13.62 %	12.58 %	13.82 %	15.44 %	17.28 %	17.82 %
Idle	62.85 %	60.37 %	55.92 %	58.15 %	53.62 %	51.86 %
Block	0.02 %	0.00 %	0.00 %	0.01 %	0.00 %	0.01 %

Table V: Statistics on the parameters of the simulation cases.

Constraints	Variables	Integers	Others	Nonzero coefficients	Total goal
235	462	311	158	958	5574852
Nodes	Remaining nodes	Reliable value	Iteration	Count	Mean total goal
1	0	5985624	215	2	5815247

To further demonstrate the effectiveness of our simulation model for joint optimization of multi-stage production scheduling, this paper compares our simulation model with a simulation model without preventive machine maintenance (model 2), and a simulation model with preventive machine maintenance, and a non-fixed early delivery period (model 3). Simulation model 2 only differs from our simulation model in that the machine capacity needs to satisfy a different constraint of the non-fixed early delivery period function. Model 3 only differs from our model in production cost.

However, the two reference simulation models adopt very different hypotheses, such that the overall objective function is inconsistent with the actual situation. Then, their results cannot be used to measure the quality of our model. To overcome the problem, this paper sets up a simulation system with the same parameters. The scheduling plans obtained by our model, and models 2 and 3 were imported to the simulation system. The simulation results were compared to demonstrate the performance of each model. Table VI shows the operation and machine sequences of products $h1$ and $h2$.

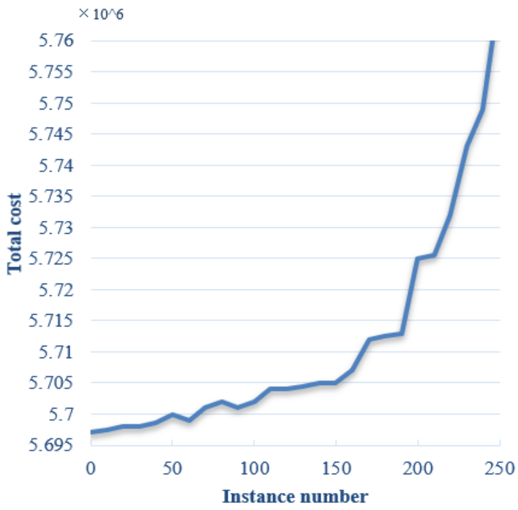

Figure 4: Distribution of calculated production costs.

Table VI: Operation and machine sequences of products $h1$ and $h2$.

Product	Operation sequence	Machine sequence
$h1$	1-2-3-4-5-6	1-2-3-4-5
$h2$	1-2-3-4-5-4	1-2-4-2-1
Product	Operation sequence	Machine sequence
$h1$	1-2-3-4-5-6-7-8-9-10-11-12-13	1-2-3-4-5-6-7-8-9-10-11-12-13-14
$h2$	1-2-6-7-5-3-4-1-6-7-8-9-8	1-2-3-4-8-4-5-6-2-4-9-1-3-6

Fig. 5 compares the costs of our simulation model and those of the two reference simulation models. Note that MSTC, MSPCC, MSEPC, SSTC, SSPCC, and SSEPC refer to multi-stage total cost, multi-stage production scheduling cost, multi-stage preventive machine maintenance cost, single-stage total cost, single-stage production scheduling cost, and single-stage preventive machine maintenance cost, respectively. As shown in Fig. 5, our model achieved the lowest values in all six costs. In the designed simulation system, our model reduced the total production cost by 18.4 % compared to model 2, and 12.7 % compared to model 3. Therefore, our simulation model has an obvious advantage and the lowest production cost. The advantage is increasingly prominent with the growing number of operations and machines. The simulation results demonstrate the necessity of global optimization of production scheduling.

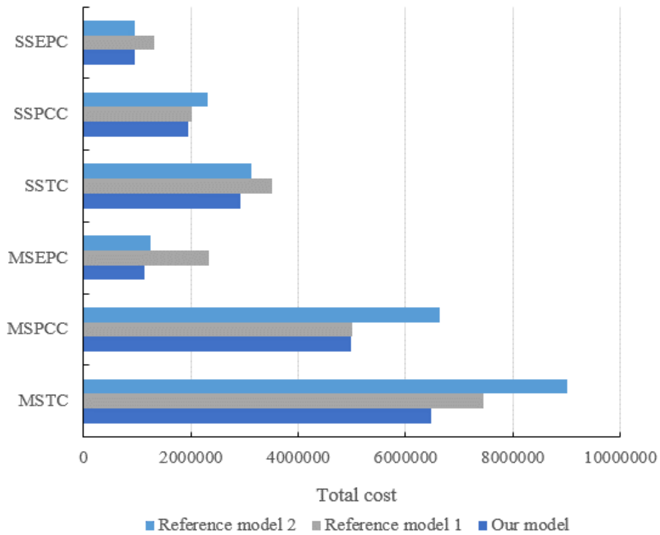

Figure 5: Cost comparison between our simulation model and reference simulation models.

6. CONCLUSIONS

This paper mainly investigates the multi-stage production scheduling optimization of automated production through simulation. To minimize material cost, inventory cost, preventive maintenance cost, and machine maintenance cost, the authors firstly illustrated the process of multi-stage production scheduling of automated production, constructed a simulation model for the automated production line, using Plant Simulation, explained the flow and objectives of the simulation, and detailed the hypotheses of the proposed simulation model. Next, a joint optimization model was constructed for the multi-stage production scheduling of automated production, from the perspective of deterministic modelling. In addition, the production task assignment for traditional pull scheduling model was improved to meet the dynamic collaborative demand for machines. Through experiments, the authors obtained the optimal solutions to simulation parameters for different production cycles, gathered the statistics on the parameters of actual production cases, and plotted the calculated production costs. These results confirm the scientific nature of striking a balance between production scheduling and decision-making of preventive maintenance. In addition, our model was compared with models 2 and 3, revealing the necessity of global optimization of production scheduling.

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