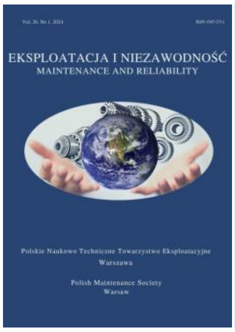

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Research on integrated scheduling of equipment predictive maintenance and production decision based on physical modeling approach

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Highlights

- Consider the impact of equipment degradation maintenance on production decisions.
- Physical modeling is used to analyze the equipment with imperfect fault data.
- An improved genetic algorithm based on hormone regulation was used to solve the problem.
- Integrating maintenance and production into a real production environment.

Abstract

Equipment performance deteriorates continuously during the production process, which makes it difficult to achieve the expected effect of production decisions made in advance. Predictive maintenance and production decisions integrated scheduling aim to rationalise maintenance activities. It has been extensively researched. However, past studies have assumed that faults obey a specific probability distribution based on historical data. It is difficult to analyse equipment that is brand new into service or has poor historical failure data. Thus, in this paper, we construct a twin model of a device based on a physical modelling approach and tune it to ensure high fidelity of the model. Degradation curves were created based on equipment characteristics and developed maintenance activities. Develop an integrated scheduling model for predictive maintenance and production decisions with the goal of minimising maximum processing time. An improved genetic algorithm is used to solve the problem optimally. Finally, apply a practical scenario to verify the effectiveness of the proposed method.

Keywords
physical modelling, degradation curve, predictive maintenance, production decisions, improved genetic algorithm

1. Introduction

Production decisions are primarily concerned with the rational allocation of resources and the sequencing of processes to optimise the desired production goals. Rational production decisions can improve efficiency, reduce costs and energy consumption, and ensure product quality and delivery[20]. However, in the actual production, it is often difficult to achieve the expected results with decisions made in advance. Mainly because of the continuous degradation of equipment performance during operation, which leads to frequent equipment failures. These failures often lead to disruption of production plans, directly affecting the implementation of production decisions and causing incalculable economic losses to the enterprise[11]. This is why is particularly important to take into account the maintenance process of the equipment in advance in the production decisions, especially in serial or process oriented production lines.

Predictive maintenance and production decision-integrated scheduling is more in line with actual needs. In recent years,

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many researchers have considered the impact of equipment maintenance on production scheduling, focusing on both single machine scheduling and line scheduling. The integration of predictive maintenance on a single machine for scheduling decisions has now been extensively studied[1,13,14,15]. Najid, NM et al.[12] established linear mixed integer programming to solve the production and maintenance integration problem, considering demand shortages and the reliability of the production line. Pan et al.[16] and Lu et al.[10] introduced the effective lifetime and maintenance lifetime of the machine to describe the degradation of the machine for the single machine scheduling model, designed improved algorithms to optimise the objectives. Liu et al.[9] proposed a model for coordinating predictive maintenance decisions with single-machine scheduling decisions based on predictive information, taking into account both machine lifetime and health affected by degradation. Yildirim and Nezami[21] considered the impact of product processing time on machine degradation and performed an experimental analysis with the objective of minimising maintenance costs and energy consumption. Zhang et al.[23] proposed a strategy that combines multitasking maintenance with production to solve the problem of idle resources and increased time cost due to maintenance in scheduling. For production lines consisting of multiple machines, the study focuses on the dependencies between the different machines, the collaboration between the equipment and the impact of predictive maintenance on the overall efficiency of the production line. Zahedi, Z. et al.[22] investigated the trade-off between production and maintenance costs for dual machine operation. Zhou and Lu[24] proposed a dynamic maintenance strategy for serial multi-device systems with high-quality integrated reliability by analysing the joint optimisation process for serial no-re-entry systems. Chen et al.[3] studied the bi-objective scheduling problem of maximum completion time and total delay time when parallel machines have flexible maintenance time and job release time, and solved it with the improved NSGA-II. Kung and Liao[7] jointly predicted the optimisation of maintenance and job scheduling problems, considered the machine productivity affected by processing time, developed a heuristic algorithm based on taboo search. Paprocka et al.[17] proposed an equipment condition assessment method with reliability characteristics. Also, Paprocka et al.[18] developed a scheduling method that reflects the operation of the production system and the nature of disturbances and applied ant colony optimisation to construct a production schedule. Ladj et al.[8] studied the process shop scheduling based health management with predictive maintenance and proposed two integrated metaheuristics to solve the problem. Ghaleb et al.[5] studied the real-time joint optimisation of maintenance planning and production scheduling, considering the problems of new order introduction, order expediting, machine degradation, and random failures.

In most of the published studies, an approach based on historical degradation data or assuming that the failure rate fits a specific probability distribution, such as the Weibull distribution, Maxwell distribution, Gamma distribution, etc., is usually used. Although some specific distributions have been validated as common distributions to describe the lifetime and failure rate of devices, However, this hypothetical approach is too coarse and has many limitations that make it difficult to describe the complex behaviour of equipment failures. And the assumed failure distribution approach usually also requires a large amount of historical failure data for parameter estimation. When failure data are incomplete, the estimation of parameters by experience can directly lead to inaccurate failure rate prediction. In this paper, the main focus is on the integrated scheduling of predictive maintenance and production decisions for devices that lack historical degradation failure data. Specifically, a framework for integrated scheduling is first proposed. Then the future state and remaining lifetime of the equipment are predicted by modelling the equipment's twin dynamics and based on the degradation curve. Rationalise maintenance activities according to the equipment status and production plan to ensure the stability and reliability of the machining process.

The overall structure of this paper is as follows: Chapter 2 introduces the integrated scheduling framework. Chapter 3 discusses the implementation of the relevant methods. Chapter 4 introduces relevant case-application scenarios. Chapter 5 verifies the validity of the proposed method and presents the results. Chapter 6 summarises the whole text and looks ahead.

2. Integrated Scheduling Framework for Predictive Maintenance and Production Decisions Making

In order to effectively manage the conflict between the maintenance needs of data-deficient equipment and production tasks, the framework shown in Figure 1 is proposed. The aim is to achieve collaborative management of maintenance and production by combining physical modelling of equipment, real-time data and optimal scheduling. The framework uses physical models to describe device behaviour and failure mechanisms, combined with data-driven predictive models to provide a reliable basis for decision makers.

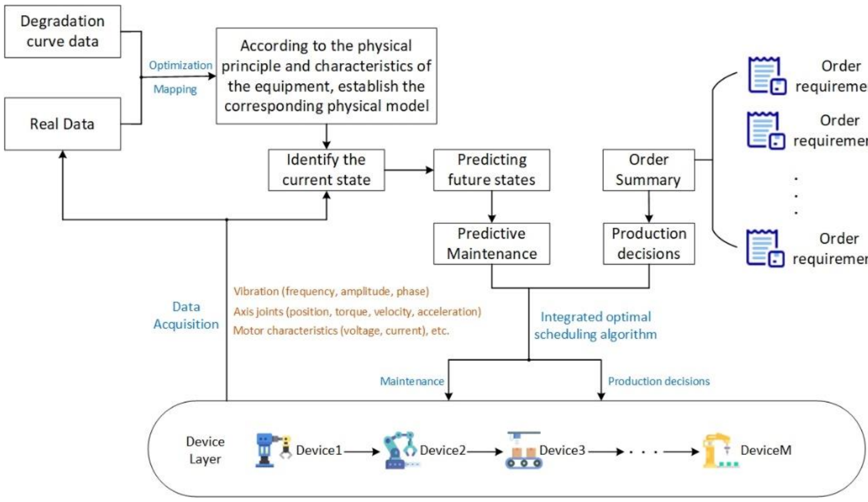

Fig. 1. Integrated scheduling framework.

The framework includes the following key components: First, the structure, operating principle, and failure mechanism of the equipment are modelled by physical modelling methods, and degradation curves are introduced. Simulation tuning of the physical model based on sensor data is performed to compensate for the insufficient historical degradation data. Second, the operating parameters of the equipment is monitored in real time to identify the current status of the equipment. The physical model is then combined with real-time data to monitor and predict equipment health status using data analysis and predictive models. Finally, the optimal scheduling algorithm is also used to determine the best maintenance time and production scheduling plan.

The integrated scheduling framework for predictive maintenance and production decision-making based on a physical modelling approach can better capture the failure characteristics and maintenance needs of equipment and provide a reliable basis for decision-making. This approach usually requires some approximations and assumptions to be made to the analytical model, which makes the model somewhat distant from the real equipment. A data-driven, machine-learning-based approach allows for more accurate health status assessments of equipment[19]. However, predictive maintenance using a physical modelling approach offers a viable option for equipment that lacks historical degradation failure data. A new idea is provided for the solution of such equipment predictive maintenance and production decision integrated scheduling problems.

The framework is applicable to both stand-alone equipment and production floor systems. By integrating physical modelling, data analysis, and optimisation methods, high equipment reliability and planning accuracy can be ensured.

3. Approach

3.1. Equipment condition prediction based on a physical modelling approach

3.1.1. Twin static model creation

To create a high-fidelity static models of equipment twins, we took the following three key steps, as illustrated in Figure 2.

The initial step is to build the twin mapping model. Firstly, the physical parameters of the equipment are collected, including dimensions, structure, connections and other performance parameters. These parameters describe the geometry and kinematic characteristics of the device. Subsequently a static model is constructed based on the equipment parameters. Take the robotic arm for example, it is possible to collect dimensional structures, joint parameters to build a geometrical model of the robotic arm. And to build a kinematic model of the robotic arm, based on the mode of movement.

The second step is to add physical characteristics. To simulate the motion of the equipment with more realism, we need to introduce physical properties. This includes considering the inertial properties of the equipment, such as mass distribution and rotational inertia. We also considered physical effects such as frictional and inertial forces and incorporated them into the static model to more accurately simulate the motion of the equipment.

The third step is to add virtual sensors. We use the static model of the equipment to simulate the measurement of the equipment by the virtual sensor and thus generate the virtual sensor data. These data can be used to monitor the status of the equipment, perform failure detection, or verify control algorithms.

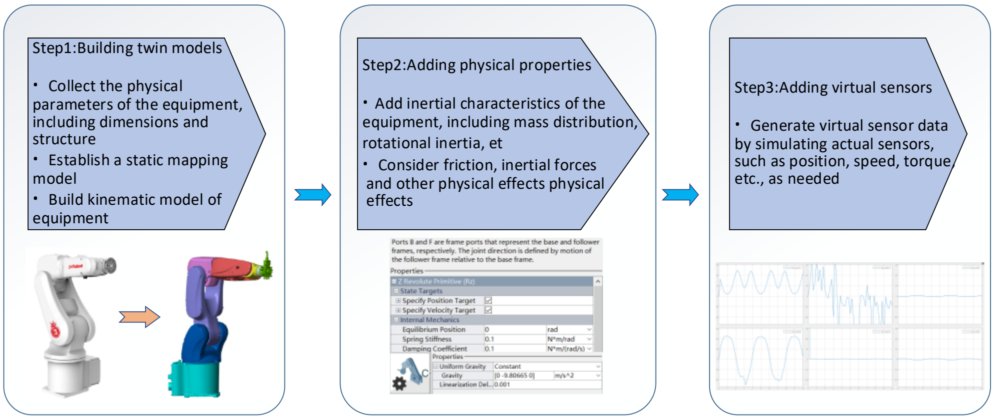

Fig. 2. The twin static model creation process.

3.1.2 Degradation curve generation

Aivaliotis et al.[2] proposed that for equipment lacking historical degradation data, the degradation curve of the corresponding equipment can be studied based on maintenance records, manufacturer data, and relevant literature. Specifically, the degradation characteristics of the equipment can be characterised based on the frequency of component replacement or relevant literature data and manufacturer's data, on the basis of which a corresponding degradation curve can be generated. These curves describe the performance trends of the equipment at different levels of degradation and provide a basis for predicting the degradation behaviour of the equipment. Finally, we map these degradation curves into the twin model. This process as shown in Figure 3.

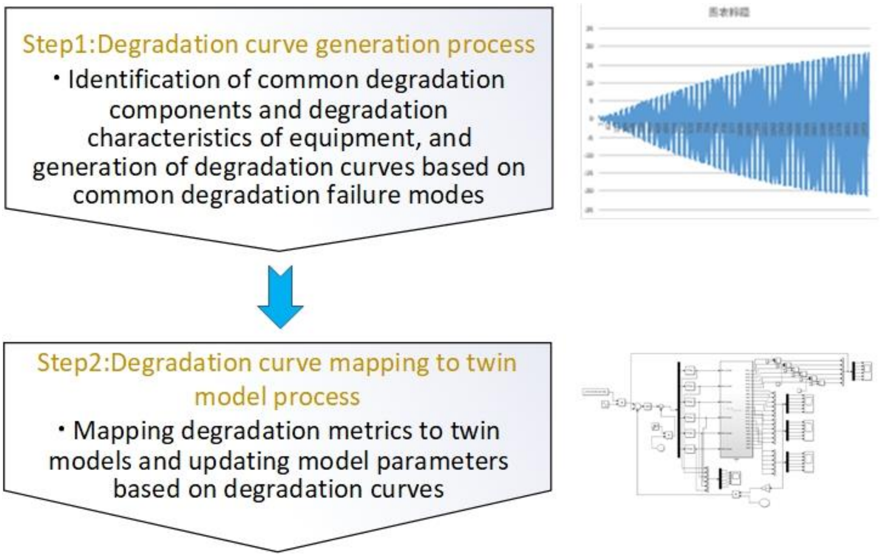

Fig. 3. Twin device degradation process.

3.1.3 Equipment status prediction

As shown in Figure 4. The model built in the first two steps extracts features from the data to determine whether the current equipment is in a normal operating state, a degraded state, or a potential fault state, providing a basis for subsequent prediction and maintenance decisions. Next, the twin model is adjusted for simultaneous simulation based on the device monitoring data. A dynamic bias compensation model between the physical data and the twin simulation data is considered to ensure high fidelity of the model. Finally, based on the above two steps of analysis, the twin model and degradation curve are combined to predict the future performance status of the equipment in order to rationalize the maintenance activities in the production process.

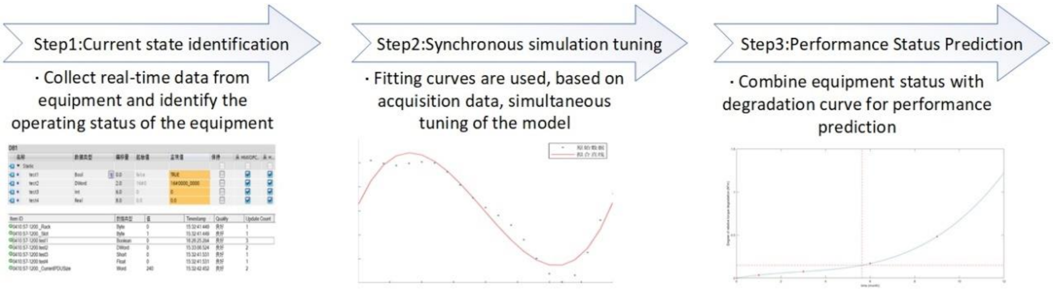

Fig. 4. Synchronous tuning and state prediction.

3.2 Predictive maintenance and production decision - integrated scheduling

This chapter focuses on the joint driving torque and jitter of the twin robotic arm as the basis for maintenance decisions, and defines the variable parameters as shown in Table 1 for the predictive maintenance and production decisions integration scheduling problem in the replacement flow shop.

Table 1. Variable parameter table.

Parameters	**Connotation of parameters**
$J = \{J_1, J_2, \dots, J_n\}$	Production Order Collection
$M = \{M_1, M_2, \dots M_m\}$	Machine Collection
$t(i,j)$	Processing time of order task j on machine i
$w(i,j)$	Waiting time between machine i processing order j and $j+1$
ϵ	Relative deviation of joint torque
μ	Ideal joint torque
μ'	Joint torque in degenerative state
ε	Shaking degree
θ	Joint torque deviation threshold
P_m	Maintenance time
T_{i1}	Machine M_i processing process time consumption
T_{i2}	Time consumed by the machine M_i maintenance process
T_i	Total time consumed by machine M_i
T_{total}	Total processing time

3.2.1. Problem Description

In the replacement flow shop, a total of n order tasks $J = \{J_1, J_2, \dots, J_n\}$, processed on m machines $M = \{M_1, M_2, \dots M_m\}$. Each order task is processed at different times on each machine, and all orders are processed in the same order on each machine. As a semi-flexible manufacturing system, the replacement shop requires a certain amount of adjustment time when configuring processes to suit different production needs. But the adjustment time is very short, and its effect is ignored here. The degradation of the robotic arm during operation is mainly reflected in the decline of the joint drive torque. When sufficient torque cannot be provided, it will affect the motion quality and control accuracy of the robotic arm, resulting in jittering and unstable control of the robotic arm. When exceeding a certain threshold, maintenance strategies need to be developed to improve equipment performance. The scheduling objective is to rationalise the maintenance strategy and optimise the workpiece machining sequence to minimise the final completion time. The entire process satisfies the following constraints:

1) At the start time, all workpieces and equipment to be machined are ready;
2) Optimal initial performance status of all equipment;
3) The start time of the subsequent order must be after the completion time of the preceding order, and the current equipment status is idle;
4) The equipment can go directly to processing after the

maintenance is completed;

The mathematical model is described as follows: Assume that $t(i,j)$ denotes the processing time of order task j on equipment i. $w(i,j)$ denotes the waiting time between the completion of order j by equipment i and the next processing. Then the total time T_{i1} consumed by machine M_i during processing is:

$$T_{i1} = \sum_{j=1}^{n} [t(i,j) + w(i,j)] \tag{1}$$

The performance degradation of the robotic arm during operation is mainly reflected in the degree of degradation of the joint torque and the degree of jitter. Specifically, the relative deviation of the torque ϵ and the degree of jitter ε are used to assess whether the equipment should be subjected to maintenance activities.

$$\epsilon = \frac{\mu - \mu'}{\mu} \tag{2}$$

Where μ is the joint torque of the equipment in optimal operation, while μ' is the joint torque in a degraded state of performance. If ϵ exceeds the deviation threshold θ, or if the magnitude and frequency of ε are outside the safety range given by the manufacturer before the order task j is processed, the equipment needs to be subjected to the corresponding maintenance activities first. Then the total time T_{i2} consumed by the maintenance activity of the equipment M_i process is:

$$T_{i2} = \sum (P_m) \tag{3}$$

Then the total time T_i consumed by equipment M_i is:

$$T_i = T_{i1} + T_{i2} \tag{4}$$

The total processing time T_{total} for this production is:

$$T_{total} = \max\{T_i \mid i = 1,2,3,\dots,m\} \tag{5}$$

The objective function is to minimize the maximum processing time:

$$\min T = \min\{T_{total}\} \tag{6}$$

3.2.2. An improved genetic algorithm based on hormonal regulation mechanism

Production scheduling is shown to be a typical class of NP-hard problems. While theoretically possible exact solutions exist, in real-world problems of large size, exponential levels of computational time are usually required. Therefore, for the solution of such problems, meta-heuristic algorithms such as genetic algorithms, particle swarm algorithms, simulated annealing algorithms, etc. Such algorithms can find suboptimal solutions in acceptable time. Genetic algorithms accounted for 45 per cent of all research[6].

Genetic algorithms are excellent in combinatorial optimisation problems. It can effectively deal with discrete decision variables and has strong global search ability. And it can deal with multiple individuals at the same time, accelerating the solution of large-scale combinatorial optimisation problems, which is widely used to solve large-scale shop scheduling problems. However, genetic algorithm also has the disadvantage of relying too much on crossover and variation links to jump out of the local optimal solution.

Based on the problem description in 3.2.1, an improved genetic algorithm based on hormone regulation mechanisms is proposed. The overall idea of the algorithm is as follows.Optimisation of initial populations using backward learning. A combination of roulette and elite retention is used to retain the best individuals while ensuring individual diversity. The algorithm is guaranteed to have global search capability by means of diverse variants. Adaptive cross-variance probabilities are designed using hormonal regulatory mechanisms. The population diversity can be maintained by a rough search in the early iterations and a detailed search in the late iterations to retain the superior individuals and improve the convergence rate. The flow chart of the algorithm is shown in Figure 5.

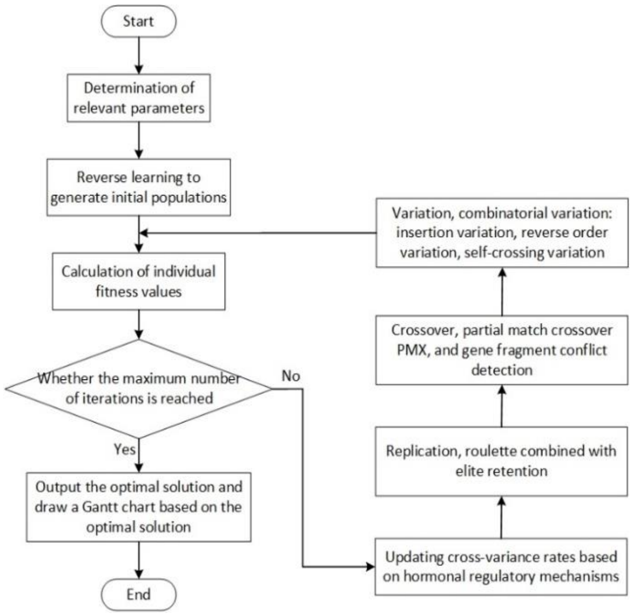

Fig. 5. Flow chart of improved genetic algorithm based on hormone regulation.

Usually the population evolution process is mainly classified into two stages:

- Pre-population evolution: large crossover probability and small variation probability, which are conducive to rapid population convergence and have the characteristic that more optimal solutions are not easily lost;
- Late stage of population evolution: small crossover probability and large variation probability are conducive to refined search and the maintenance of population diversity.

The deficiencies of conventional GA were improved by introducing hormonal regulation mechanisms. The hormone regulation rise function and fall function law equations are:

$$F_{up}(G) = \frac{G^n}{T^n + G^n} \tag{7}$$

$$F_{down}(G) = \frac{T^n}{T^n + G^n} \tag{8}$$

where G is the function independent variable; T is the threshold and $T > 0$; n is the Hill coefficient and $n \geq 1$; n and T jointly determine the slope of the curve. The function has monotonicity and non-negativity. If hormone x is regulated by hormone y, then the relationship between the rate of secretion S_x of hormone x and the concentration C_y of hormone y is:

$$S_x = \alpha F(C_y) + S_{x0} \tag{9}$$

where S_{x0} is the basal secretion rate of hormone x; α is a constant factor.

If the average fitness of the current population is high, it indicates that the diversity of the population is low, and at this time, the crossover rate should be reduced and the variation rate increased to increase the population diversity. On the contrary, it is necessary to increase the ability of population exploration. Adaptive crossover probability factors can be designed based on hormonal regulation laws:

$$P_c = 1 - P_c^0 \left[1 + \alpha \frac{(f_{av})^{n_c}}{(f_{max} - f_{min})^{n_c} + {f_{av}}^{n_c}}\right] \tag{10}$$

Adaptive variation probability factor:

$$P_m = P_m^0 \left[1 + \beta \frac{(f_{av})^{n_m}}{(f_{max} - f_{min})^{n_m} + {f_{av}}^{n_m}}\right] \tag{11}$$

(10) and (11) in which P_c^0 and P_m^0 represent the initial crossover probability and the initial variance probability, respectively; f_{av} represents the adaptation mean; f_{max} and f_{min} represent the maximum and minimum values of fitness in each generation of individuals, respectively; α、β、n_c、n_m are coefficient factors.

4. Case study

4.1. Scene Introduction

Taking an actual customised assembly workshop as an example. In this workshop, many different types of products can be processed by switching machine processes. The type of order is mostly small batch customised processing, the type of product processed varies from order to order, and the time spent on each process is also different. This workshop is characterised by semi-flexible production and is a classic flow shop. In this case study, the equipment data is collected through the sensors in the controller, specifically the drive torque of the joint axes, to achieve monitoring of the equipment status. The scene model of the assembly workshop and the twin model of the robotic arm are shown in Figure 6.

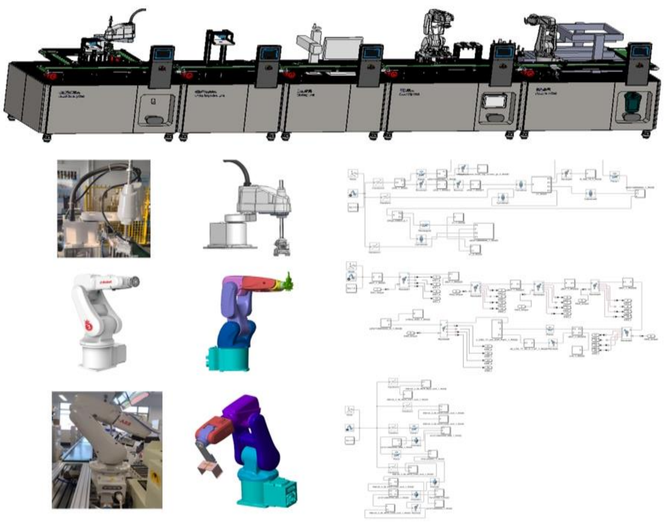

Fig. 6. Assembly workshop scene and twin model of robotic arm.

In Simscape, the robotic arm model is constructed by connecting the rigid body to each axis of rotation. Constrain the twin model by obtaining the range of motion of the robotic arm from the manufacturer, and the maximum single-axis speed. The input to the robotic arm twin static model is the position information of each joint axis, which is converted into torque information to drive the model's motion. From the manufacturer, it is known that the robotic arm, especially during long-term operation, can cause instability in the drive torque control due to bearing and gear wear, which can affect the quality of the product assembly or processing. And from some related robotic arm studies, it can also be considered that bearings are the most vulnerable to failure. Bearings can account for up to 44% of the total number of failures in some equipment[4]. For the failure mechanism of bearing and gear wear, the modeling of the wear process is realized by introducing the Coulomb viscous friction model.

Table 2. Processing Schedule.

scale	Order Number	(Process, processing time/min)				
Small scale	J_1	(1,116)	(2,125)	(3,137)	(4,104)	(5,157)
	J_2	(1,139)	(2,99)	(3,178)	(4,143)	(5,101)
	J_3	(1,144)	(2,148)	(3,131)	(4,136)	(5,91)
	J_4	(1,127)	(2,179)	(3,111)	(4,155)	(5,117)
	J_5	(1,139)	(2,116)	(3,148)	(4,118)	(5,109)
	J_6	(1,90)	(2,177)	(3,175)	(4,102)	(5,151)
	J_7	(1,168)	(2,119)	(3,122)	(4,140)	(5,124)
	J_8	(1,119)	(2,153)	(3,101)	(4,136)	(5,111)
	J_9	(1,86)	(2,163)	(3,145)	(4,94)	(5,95)
	J_{10}	(1,148)	(2,97)	(3,133)	(4,165)	(5,178)
	J_{11}	(1,111)	(2,178)	(3,106)	(4,127)	(5,89)
	J_{12}	(1,99)	(2,137)	(3,156)	(4,174)	(5,154)
	J_{13}	(1,158)	(2,117)	(3,157)	(4,97)	(5,126)
	J_{14}	(1,159)	(2,109)	(3,163)	(4,148)	(5,117)
	J_{15}	(1,178)	(2,163)	(3,85)	(4,116)	(5,105)
	J_{16}	(1,157)	(2,111)	(3,132)	(4,155)	(5,103)
	J_{17}	(1,139)	(2,158)	(3,175)	(4,139)	(5,108)
	J_{18}	(1,174)	(2,128)	(3,106)	(4,173)	(5,83)
	J_{19}	(1,146)	(2,113)	(3,114)	(4,88)	(5,85)
	J_{20}	(1,171)	(2,146)	(3,167)	(4,168)	(5,177)
Medium scale	J_{21}	(1,134)	(2,86)	(3,167)	(4,182)	(5,161)
	J_{22}	(1,112)	(2,165)	(3,74)	(4,81)	(5,174)
	J_{23}	(1,163)	(2,168)	(3,63)	(4,170)	(5,189)
	J_{24}	(1,121)	(2,145)	(3,187)	(4,81)	(5,165)
	J_{25}	(1,175)	(2,64)	(3,135)	(4,92)	(5,174)
	J_{26}	(1,192)	(2,221)	(3,73)	(4,48)	(5,187)
	J_{27}	(1,144)	(2,130)	(3,155)	(4,168)	(5,192)
	J_{28}	(1,129)	(2,187)	(3,112)	(4,176)	(5,169)
	J_{29}	(1,152)	(2,124)	(3,211)	(4,174)	(5,72)
	J_{30}	(1,155)	(2,196)	(3,161)	(4,180)	(5,154)
Large scale	J_{30}	(1,150)	(2,131)	(3,189)	(4,140)	(5,137)
	J_{31}	(1,189)	(2,169)	(3,158)	(4,71)	(5,170)
	J_{32}	(1,148)	(2,156)	(3,88)	(4,167)	(5,146)
	J_{33}	(1,131)	(2,124)	(3,122)	(4,187)	(5,162)
	J_{34}	(1,112)	(2,185)	(3,163)	(4,114)	(5,132)
	J_{35}	(1,159)	(2,177)	(3,195)	(4,159)	(5,148)
	J_{36}	(1,141)	(2,120)	(3,181)	(4,165)	(5,120)
	J_{37}	(1,192)	(2,148)	(3,126)	(4,193)	(5,63)
	J_{38}	(1,128)	(2,159)	(3,110)	(4,181)	(5,120)
	J_{39}	(1,166)	(2,133)	(3,134)	(4,88)	(5,65)
	J_{40}	(1,159)	(2,137)	(3,167)	(4,139)	(5,130)

In the case of joint scheduling problems, a week's production tasks are usually scheduled at the same time, that is, 20 production orders. However, in order to compare the effectiveness of the proposed algorithm under different case sizes, three scenarios of small-scale processing, medium-scale processing and large-scale processing are set up in this chapter.The processing schedule is shown in Table 2. It should be noted that the maintenance interval of the robotic arm for bearings and gears is usually 1–3 months. However, for the scheduling of a week's production tasks, from time to time, we encounter time points that require maintenance. In practise, the current status of the equipment needs to be identified to allow for more accurate scheduling of maintenance activities. This paper is only a theoretical illustration, assuming that in this production schedule, the equipment performance declines to an unacceptable state and the maintenance overhaul time is set to 6 hours based on experience.

4.2 Design of orthogonal experiments to determine hormone coefficient factors

The value of the parameter $P_c^0, P_m^0, \alpha, \beta, n_c, n_m$ in the adaptive cross-variance operator directly affects the range of values of the cross-variance rate, the increase and decrease. Rational design of parameters can ensure the efficiency and diversity of the search process. The estimation of parameters only by empirical means is highly uncertain. Orthogonal experiments were designed to ensure the reasonableness of the crossover variability. Table 3 shows the processing schedule selected for the orthogonal experiments. The data is mainly derived from the shop floor scheduling public dataset case flowshop1 provided by OR-Library.

Table 3. The processing schedule selected for the orthogonal experiment.

	M_1	M_2	M_3	M_4	M_5
J_1	59	37	67	39	30
J_2	89	41	42	59	43
J_3	18	56	75	95	75
J_4	65	67	50	57	13
J_5	1	79	71	78	88
J_6	49	100	30	76	36
J_7	99	9	34	44	62
J_8	35	46	58	26	73
J_9	8	98	97	20	73
J_{10}	39	73	20	55	30
J_{11}	60	18	97	61	22
J_{12}	71	1	4	88	52
J_{13}	20	22	7	3	28
J_{14}	44	30	55	68	92
J_{15}	29	89	12	96	71
J_{16}	54	12	21	74	2
J_{17}	62	96	61	79	53
J_{18}	50	13	48	40	37
J_{19}	89	69	57	1	70
J_{20}	50	56	8	67	46
J_{21}	32	24	23	87	62
J_{22}	12	88	64	14	13
J_{23}	35	57	78	99	80
J_{24}	70	76	53	2	19
J_{25}	79	22	77	74	95

Five experiments were conducted for each of the nine sets of orthogonal parameters based on experience, with an initial population size of 50 and a maximum number of iterations of 500 during the experiment.The orthogonal numerical experimental parameters and experimental results are shown in Table 4. The parameters are chosen to ensure that the crossover rate and the variation rate are within the appropriate intervals.

The optimal solution and the optimal number of iterations for each orthogonal parameter in Table 4 are averaged, and the results are shown in Figure 7. The values of parameters P_c^0 and α will directly affect the coverage of the crossover rate. And the parameters P_m^0 and β will directly affect the coverage of the variability. From the results in Table 4 and Figure 7, it can be observed that the solution accuracy and optimal number of iterations for the fifth group of parameters are significantly better than the other groups of parameters. Therefore, the initial crossover rate P_c^0 can be determined as 0.6, α as 0.15, the initial variability P_m^0 as 0.1, and β as 20.

Table 4. Parameters and results of orthogonal numerical experiments.

	1	2	3	4	5	6	7	8	9
P_c^0	0.5	0.5	0.5	0.6	0.6	0.6	0.7	0.7	0.7
P_m^0	0.05	0.1	0.2	0.05	0.1	0.2	0.05	0.1	0.2
α	0.1	0.1	0.1	0.15	0.15	0.15	0.2	0.2	0.2
β	15	20	25	15	20	25	15	20	25
n_c	4	4	4	4	4	4	4	4	4
n_m	4	4	4	4	4	4	4	4	4
Optimal Solution	1483 1496 1483 1494 1488	1483 1502 1483 1483 1485	1520 1521 1507 1504 1537	1483 1483 1483 1493 1494	1483 1483 1483 1483 1483	1517 1497 1515 1501 1511	1489 1486 1494 1494 1486	1483 1486 1486 1492 1483	1497 1511 1513 1502 1520
Optimal Iterations	394 354 372 214 168	343 239 181 106 144	168 364 167 292 157	73 206 322 172 66	97 60 157 255 58	69 263 260 133 396	255 346 118 271 165	241 212 72 491 469	396 74 458 428 153

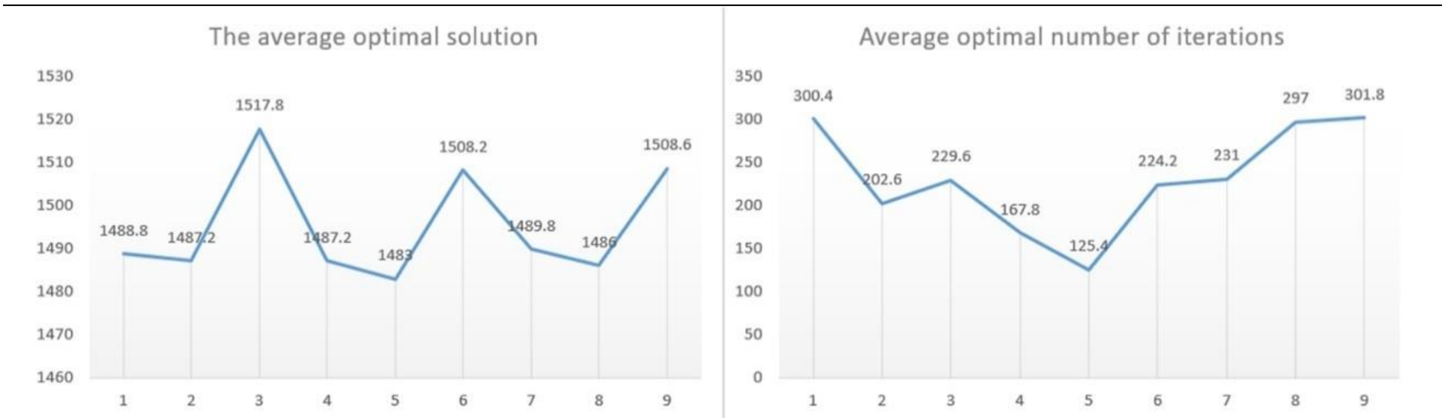

Fig. 7. Average optimal solution and average optimal number of iterations.

5. Results & discussion

Since different robotic arms are studied in the same way, the most complex six-axis robotic arm in the system is used as an example to analyse the results. The joint drive torque of the six-axis robotic arm joint axis 3 at different operating cycles is shown in Figure 8. Where M0 is the wear-free curve obtained by taking the joint cycle moment of the robotic arm in the best operating condition and performing several iterations. M1 (blue line), M3 (green line), and M6 (cyan line) are the joint axis 3 drive torque curves of the robotic arm after one month, three months, and six months of actual operation, respectively.

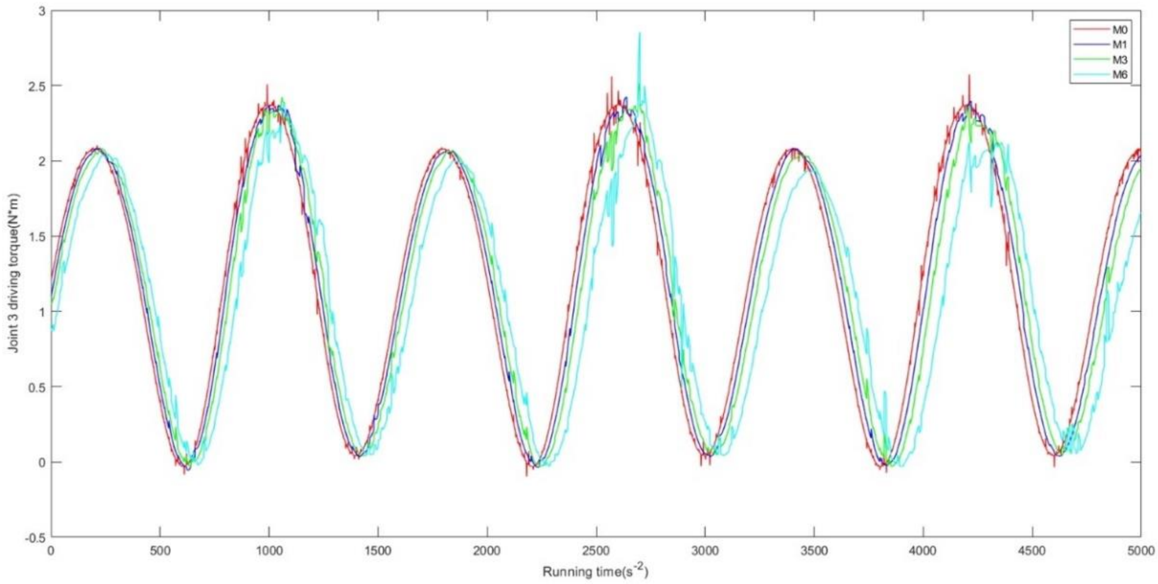

Fig. 8. Six-axis robotic arm (axis 3) joint drive torque.

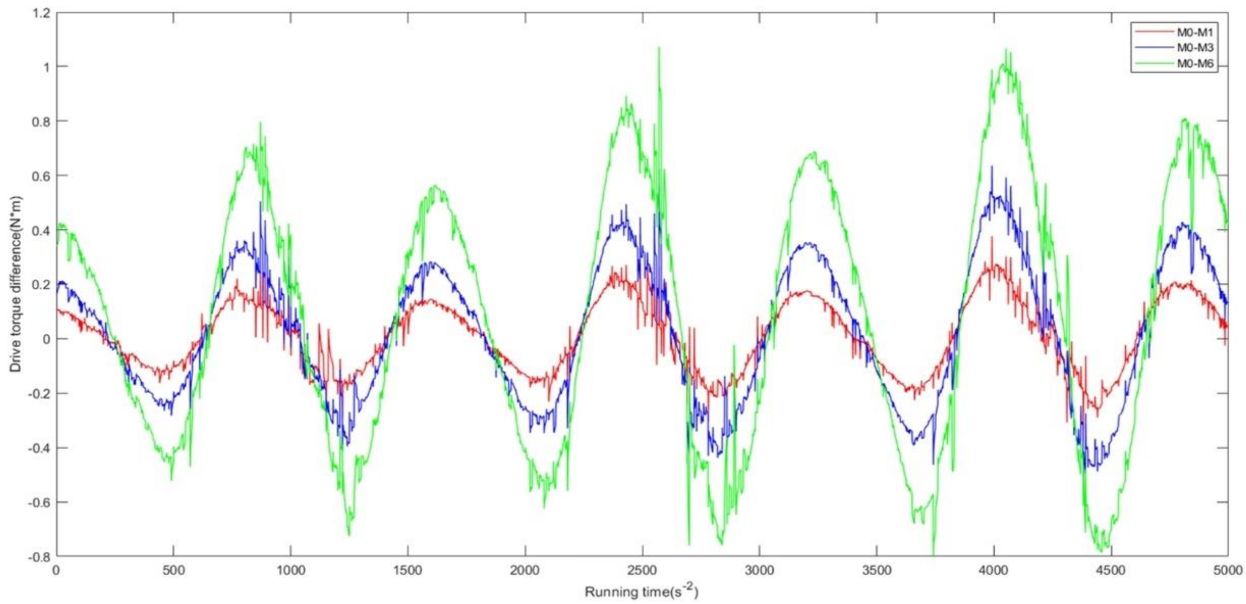

Fig. 9. Difference between M1, M3, M6 and optimum drive torque.

Figure 9 shows the difference between the joint cycle torque during the operation of the equipment for different periods of time and the optimal operating condition. From the figure, it can be seen that the difference between the joint torque and the torque in the best operating condition during a long period of operation becomes more and more obvious, and as the controller drive torque decreases, the high load of the original task intensity may even cause the robot arm control to jitter, thus affecting the processing and assembly quality of the product.

Figure 10 shows the average relative deviation of the drive torque of the joint axis 3 of the six-axis robotic arm during long-term operation, specifically the relative deviation of the average value of the torque in one cycle per month from the average value of the torque in one cycle during optimal operation. Due to the existence of the wear accumulation effect, the longer the operation time of the robotic arm, the faster the degradation of the arm, which is basically consistent with the lifetime distribution of the actual robotic arm. If the relative deviation of the torque is higher than the threshold value of 0.15 N*m, the quality of the processed product is considered to be lower than acceptable. For the quality of the product and the reliability of the equipment, it is necessary to carry out the corresponding maintenance and repair activities.

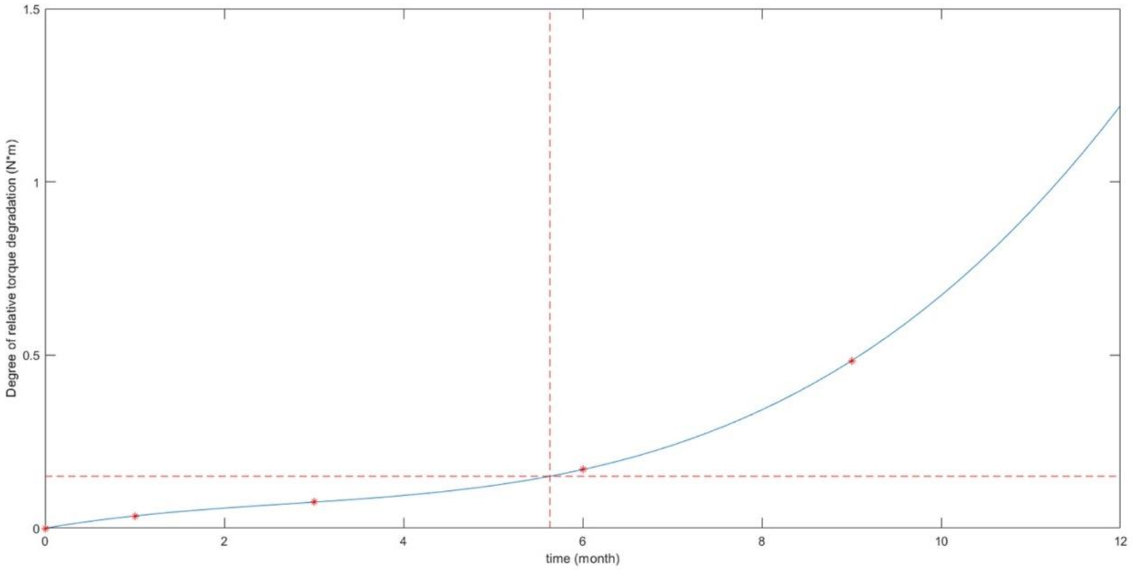

Fig. 10. Average relative deviation of drive torque.

Scheduling of orders of different sizes using improved genetic algorithms. Where the initialised population size is 50 and the number of iterations is 500. The improved genetic algorithm IGA is compared with GA, PSO, SA, and the optimal results are taken after running each of the four algorithms five times. The minimum processing times for the four algorithms for different order sizes are obtained as shown in Table 5.

Table 5. Minimum processing time for different scales.

	IGA	GA	PSO	SA
Small scale	3594	3686	3666	3618
Medium scale	5168	5329	5381	5277
Large scale	6808	6926	2967	6904

Focus on small order analysis.The maximum completion time of the generation scheduling scheme of IGA is 3594 min and the simulation runtime is 18.792s; the maximum completion time of GA is 3686 min and the simulation runtime is 8.261s; the maximum completion time of PSO is 3666 min and the simulation runtime is 6.241s; the maximum completion time of SA is 3618 min and the simulation runtime is 12.269s. The iterative optimisation process is shown in Figure 11. The initial solution quality of IGA is significantly better than the other three algorithms, and the improved genetic algorithm is convergent as a whole; it converges faster, has better stability, and is less likely to fall into local optimal solution. The scheduling Gantt charts of the three algorithms are shown in Figures 12, 13, 14, and 15 respectively. PM in the chart represents the maintenance process.

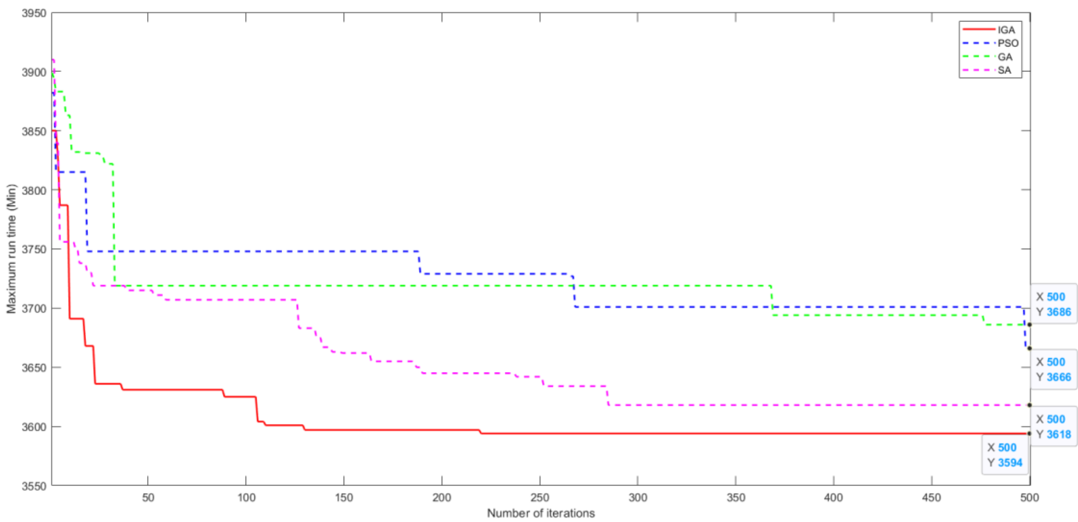

Fig. 11. Algorithm iterative optimization process. (small scale).

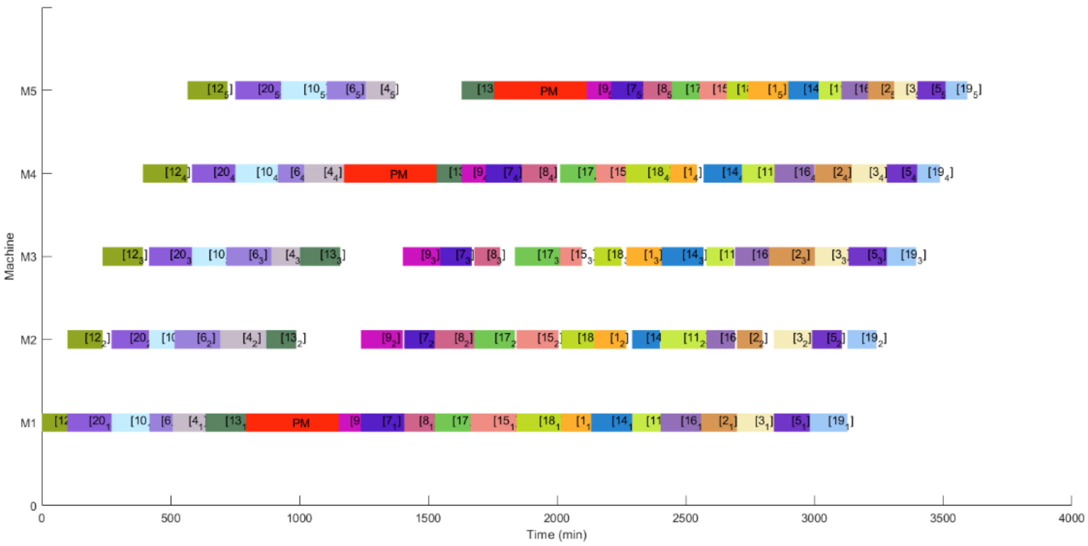

Fig. 12. IGA Optimal Gantt Chart.

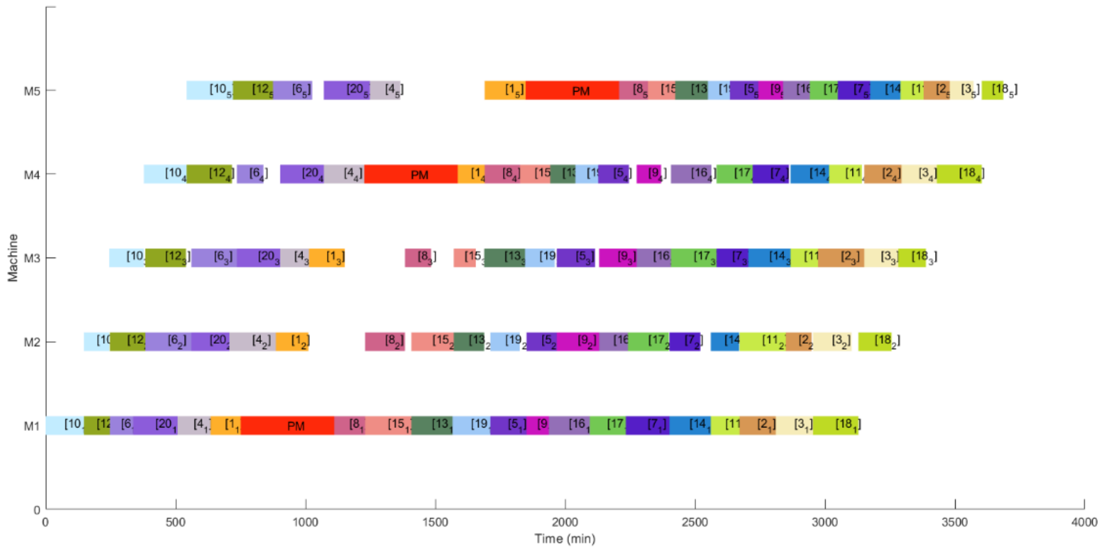

Fig. 13. GA Optimal Gantt Chart.

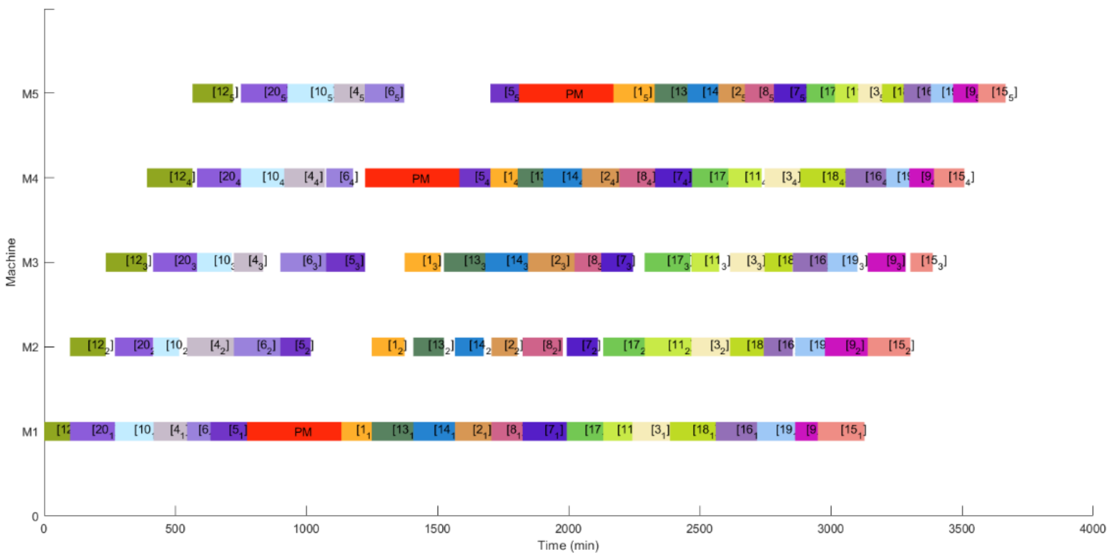

Fig. 14. PSO Optimal Gantt Chart.

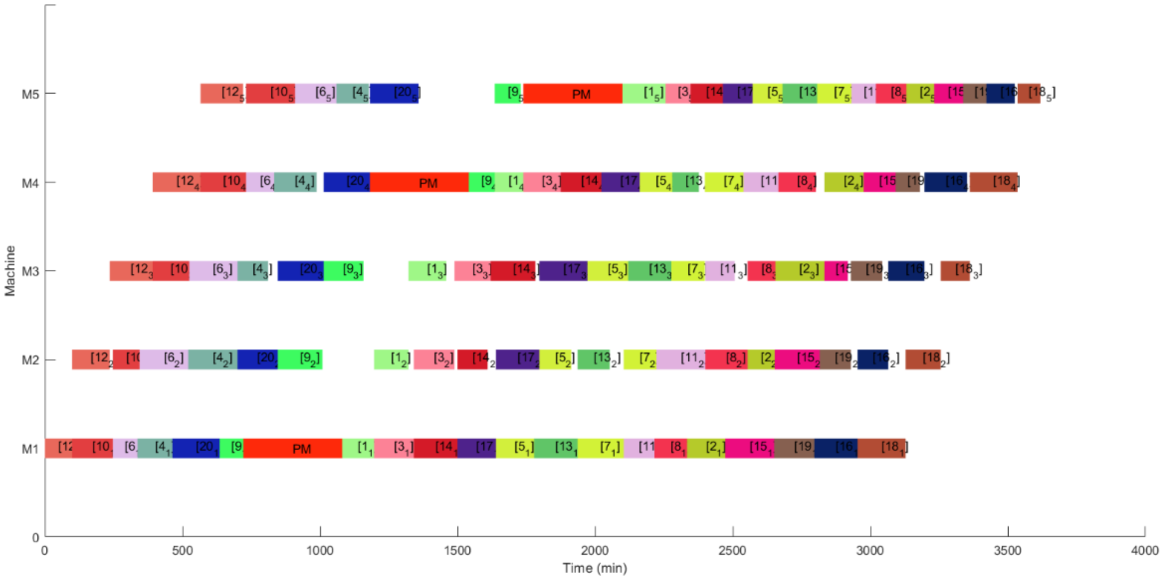

Fig. 15. SA Optimal Gantt Chart.

6. Conclusion & Outlook

This paper proposes an integrated scheduling strategy for predictive maintenance and production decisions based on a physical modeling approach, in which physical modeling, degradation feature identification, degradation curve extraction, and equipment performance state prediction are used to compensate for the lack of historical data for equipment that lacks historical degradation failure data. In considering integrated scheduling, the problem is solved by an improved genetic algorithm with hormone regulation mechanisms. Orthogonal experiments are designed to determine the values of the algorithm parameters. Comparing IGA with GA, PSO and SA, the results show that the optimal scheduling scheme of IGA is completed 92 minutes earlier than GA, 72 minutes earlier than PSO, and 24 minutes earlier than the SA.

The approach through physical modelling is slightly better in scenario applicability and analysis accuracy than the approach assuming a probability distribution of failures, but it cannot be compared to the data-driven approach based on machine learning as the main strategy. This is mainly due to the fact that physical modelling identifies only the most vulnerable failure characteristics and ignores the possibility of sudden equipment failures. Therefore, the prediction of equipment performance status based on the physical modelling approach can only make a general judgement as a next-best option in the absence of historical data. When the equipment has accumulated a certain amount of historical degradation data, based on the combination of machine learning and digital twins, and through the dynamic scheduling strategy to adjust the conflict between maintenance and production in real time, to minimise the impact of maintenance activities on the production decision-making, and to achieve the maximisation of the economic benefits of the enterprise.

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