

Received February 17, 2020, accepted February 25, 2020, date of publication March 2, 2020, date of current version March 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2977667

Integrated Intelligent Green Scheduling of Predictive Maintenance for Complex Equipment based on Information Services

SHANGHUA MI¹, YIXIONG FENG^{ID}¹, HAO ZHENG², ZHIWU LI^{ID}³, (Fellow, IEEE),
YICONG GAO¹, AND JIANRONG TAN¹

¹State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University, Hangzhou 310027, China

²Hangzhou Innovation Institute, Beihang University, Hangzhou 310052, China

³Institute of Systems Engineering, Macau University of Science and Technology, Macau 999078, China

Corresponding author: Yixiong Feng (fyxtv@zju.edu.cn)

This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFB1700804, in part by the National Natural Science Foundation of China under Grant 51775489 and Grant 51805472, and in part by the Zhejiang Provincial Natural Science Foundation of China under Grant LZ18E050001.

ABSTRACT As an important link to guarantee normal industrial production, equipment maintenance plays an increasingly key role in enhancing the competitiveness of enterprises and supporting green smart manufacturing. This paper aims to promote the implementation of predictive maintenance for complex equipment and improve the green performance of the maintenance service process. A structural framework of information sharing and service network is introduced to build a ubiquitous state data awareness environment for predictive maintenance service. Subsequently, an integrated mathematical problem model that consists of carbon emission objective and extended maintenance cost objective is constructed. Then an improved NSGA-II algorithm is utilized to solve this complicated two-objective optimization problem. In response to deal with the uncertainties of maintenance service environment and inaccuracy of prediction, a data-driven dynamic adjustment strategy is applied. A grinding roll fault case of a large vertical is used to demonstrate the effectiveness of this proposed approach.

INDEX TERMS Predictive maintenance, complex equipment, green manufacturing, information service network, integrated multiobjective optimization.

I. INTRODUCTION

The complex equipment with characteristics, such as complex product structure, a large number of components, multidisciplinary technologies and long product life cycle, is usually the core of industrial manufacturing process. As the competition among enterprises is becoming cumulatively fierce caused by external market environment changes including globalization and individualized customer needs, timely and effective complex equipment maintenance security is increasingly valued by enterprises. Meanwhile, confronted with mounting energy and environmental pressure, governments around the world have increased their focus on green growth and low carbon development of the industrial sector. Driven by increasing competitive pressures and stricter

environmental regulations, green manufacturing has been the inevitable trend [1]. Green manufacturing requires to take measures to minimize negative environmental impacts (such as carbon emissions) in three related levels of manufacturing enterprises, the product, the process and the system [2]–[4]. Equipment maintenance is an important link to guarantee the normal industrial production process and also a potential optimized object of process planning for green manufacturing as well. By providing scientific and timely maintenance, the equipment state can be guaranteed and energy efficiency can be improved. By avoiding non-value added and redundancy maintenance operations, it can reduce the consumption of resources such as spare parts and consumables. By combining maintenance planning with green manufacturing optimization objectives in different industrial scenarios, resource and energy consumption, and pollutant emission can be further optimized.

The associate editor coordinating the review of this manuscript and approving it for publication was Guanjun Liu^{ID}.

In the field of equipment maintenance, predictive maintenance is gradually replacing the passive maintenance and preventive maintenance [5], [6]. With the help of modern technologies like sensors, communication networks, and data mining, equipment current health state and the predictive information for a period of future time can be obtained to support more scientific and more flexible maintenance planning [7]. A lot of research has been done on key support technology and application technology of predictive maintenance which include equipment condition monitoring and signal processing technologies [8]–[12], equipment fault diagnosis and prediction technologies [13]–[15] and predictive maintenance scheduling optimization technologies [6], [16], [17]. In the field of maintenance scheduling, the maintenance opportunity and the maintenance resource scheduling scheme are often considered as two different optimization problems in [18]–[20]. These researches neglected the development of detailed maintenance service resource scheduling solutions when choosing the appropriate maintenance service execution opportunity. The selected maintenance time node will be inapplicable if constraints of maintenance service resources are not considered. On the theme of green manufacturing, some valuable research results have also demonstrated the positive impact of predictive maintenance. Rødseth et al. developed the profit loss indicator as a key performance criterion to measure green manufacturing state and demonstrated that the data-driven predictive maintenance strategy has a positive impact on green manufacturing by a case study of the sawmill industry [5], [21]. Yao et al. proposed a joint maintenance and energy management method and the saving of power cost is verified in an automotive assembly line [22]. Reasonable maintenance strategies can be implemented to reduce the hydraulic oil consumption of machine tools based on monitoring and prediction [23]. In the semiconductor industry, predictive maintenance strategies for lenses can be utilized to reduce waste of energy and materials and hence increase the sustainability [24]. However, the existing research focuses more on the indirect reduction of energy consumption and material consumption by planning appropriate maintenance time. The optimization of energy consumption and carbon emission caused by the maintenance scheduling and service process is ignored. For complex equipment that involve multidisciplinary technologies and various types of components from different sources, maintenance services for many fault types require long maintenance cycle and multiple resource scheduling and utilization, the optimization of energy consumption and carbon emission of maintenance service process has important significance for promoting green manufacturing. There is a research gap in integrated optimization method for maintenance opportunity and maintenance resource scheduling scheme of predictive maintenance for complex equipment under the background of green manufacturing.

Currently, some factors limit the successful implementation proportion of predictive maintenance for complex equipment [25], [26]. To monitor and analyze all potential fault

types of the target complex equipment will bring tremendous cost pressure and technical pressure for individual user enterprises. Moreover, acquiring every possible fault mode from one asset is very unlikely, and thus the fault sample data of a single enterprise is often inadequate and the prediction accuracy is limited. Meanwhile, a dynamic production environment also requires improving the adaptability of predictive maintenance decision-making. Hence, timely and reliable environment information of maintenance scheduling are needed. Fortunately, the new generation of information technology trigger changes in many related fields include predictive maintenance scheduling [27]. Equipment and available maintenance resources state data can be timely and effectively collected with the help of technologies like wireless sensor networks, internet of things, digital twin, and cyber-physical systems and data mining. Moreover, manufacturing enterprises, user enterprises and service enterprises with different spatial distribution are organized into a service network. It supports information sharing of the fault knowledge and collaborative predictive maintenance service in a larger schedulable range. Under this background, based on timely and adequate information, detailed predictive maintenance plan can be further optimized, green indexes of the scheduling process can be measured. The popularization and application predictive maintenance can be promoted as well.

Based on above analysis, some related technical/methodological contributions have been carried out in this paper, which are summarized as follows.

- A structural framework of information sharing and service network for predictive maintenance scheduling of complex equipment is discussed. Compared with the traditional way of implementing predictive maintenance, this framework is designed to support the efficient organization and flexible configuration of dispersed user enterprises and service resource suppliers, and conduct the environment for the integration and comprehensive analysis of data. The major advantages are described as follows: (1) The interconnection of user enterprises will break the information barrier, provide the opportunity of peer-to-peer evaluation, and achieve the accumulation of fault and prediction data. Based on the shared information resource, the accuracy of fault diagnosis and prediction information will be improved for these enterprises, and the technical difficulty will be reduced; (2) The construction of a service network that includes user enterprises and maintenance service resource suppliers from different spatial distribution will promotes the sharing of maintenance resources, and expands the schedulable range. With the help of effective collaborative management and allocation methods, the efficiency and the quality of maintenance services are guaranteed and improved, inventory cost pressure and technical pressure of user enterprises are further alleviated as well; (3) Based on the information perception of the whole process of resource scheduling, carbon emission prediction of maintenance scheduling process is supported.

These positive effects will be a huge driving force for the implementation of predictive maintenance with low carbon emissions in enterprises.

- An integrated intelligent green scheduling optimization method of predictive maintenance for complex equipment is proposed. A mathematical problem description model under the ubiquitous state data awareness environment is constructed for the optimization solution of predictive maintenance plans. In order to improve the feasibility, the maintenance opportunity and the maintenance resource scheduling scheme are combined in the optimization object. Two optimization objectives are provided. The global maintenance cost is the first one and the added additional economic benefits obtained by improving the efficiency and quality of subsequent production tasks are considered in it. Carbon emissions during maintenance resource scheduling process is the second one. An improved NSGA-II algorithm is put forward to solve this complicated two-objective optimization problem. A data-driven dynamic adjustment strategy for predictive maintenance decisions is utilized to respond to uncertainties of maintenance service environment and inaccuracy of prediction. Driven by real-time data, the maintenance service plan which includes necessary maintenance resources and the appropriate maintenance service time node is updated at the right time based on this strategy. Through the data-driven dynamic adaptive adjustment strategy, the joint optimization solution of the maintenance opportunity and the scheduling scheme of shared maintenance resources, and the optimization objective function which more matches the actual circumstances, accuracy, performance, and flexibility of predictive maintenance decision can be improved. The performance potential of green manufacturing can be further tapped at the process level as well.
- A case problem is solved by applying the proposed method. The better adaptability of predictive maintenance decisions under this framework to various uncertainty of maintenance service environment is verified.

The remainder of this paper is organized as follows. Section 2 introduces the structural framework of information sharing and service network. Section 3 constructs the integrated mathematical problem description model for predictive maintenance scheduling, and an improved NSGA-II and a data-driven dynamic adaptive adjustment strategy are utilized to solve the final predictive maintenance plan. Then, the case analysis is illustrated in Section 4. Finally, Section 5 concludes this paper.

II. AN STRUCTURAL FRAMEWORK OF INFORMATION SHARING AND SERVICE NETWORK FOR PREDICTIVE MAINTENANCE

The corresponding maintenance scheduling and service process is complicated since complex equipment involves multidisciplinary technologies and various types of components

from different sources [28]. In this section, a structural framework of information sharing and service network for target equipment and distributed maintenance resources is introduced to create a ubiquitous maintenance decision and scheduling environment, and types of data need to be collected which impact maintenance service performance and corresponding carbon emissions is described. This framework supports a more accurate prediction of performance for predictive maintenance plans based on the real-time interactive capability between the cyberspace layer and the physical space layer. Meanwhile, it also promotes the interactive sharing of data across organizational boundaries and supports the efficient organization and flexible configuration of dispersed user enterprises and service resource suppliers.

The proposed framework is conducted from three function layers, i.e., the physical space function layer, local function layer of the cyberspace, and cloud function layer of the cyberspace, as shown in Fig.1.

A. THE PHYSICAL SPACE FUNCTION LAYER

In the physical space function layer, state awareness of target equipment objects and related maintenance service resource objects are independently completed by the corresponding object owners. With the wave of automation, digitalization and intellectualization upgrading in recent years, some data collection and analysis functions (such as processing parameter acquisition and product quality parameter acquisition) have been implemented by service suppliers and manufacturing enterprises. By reusing and enhancing these functions, the physical space function layer can be constructed. Data acquisition objects include target equipment, production environment of target equipment, necessary maintenance resources (such as maintenance service tools, technicians, consumable and components, etc.), and scheduling environment of maintenance resources. Therefore, four types of data need to be collected, i.e., the operating data of target equipment objects, the working environment data, the state data of service resource objects, and the scheduling environment data. Data sources include sensors, controllers, energy monitors, enterprise information systems, internet, etc. Implementing sensor-based state monitoring of equipment or manufacturing processes will encounter many issues like hardware and software investment cost, sensor selection, and sensor placement. Some indirect methods have been displayed to collect state feature parameters of the target equipment object under the insufficient sensor condition [29]. The key supporting technologies of this layer include sensor selection and deployment technologies, internet of things technology, collection and transmission technologies for different data types.

B. LOCAL FUNCTION LAYER OF THE CYBERSPACE

The collected original data in the physical space function layer are isolated and littery. These data will be stored in a temporary database. The local function layer of the cyberspace offers data preprocessing capacity and plays as the data buffer and filter. The key supporting technologies of

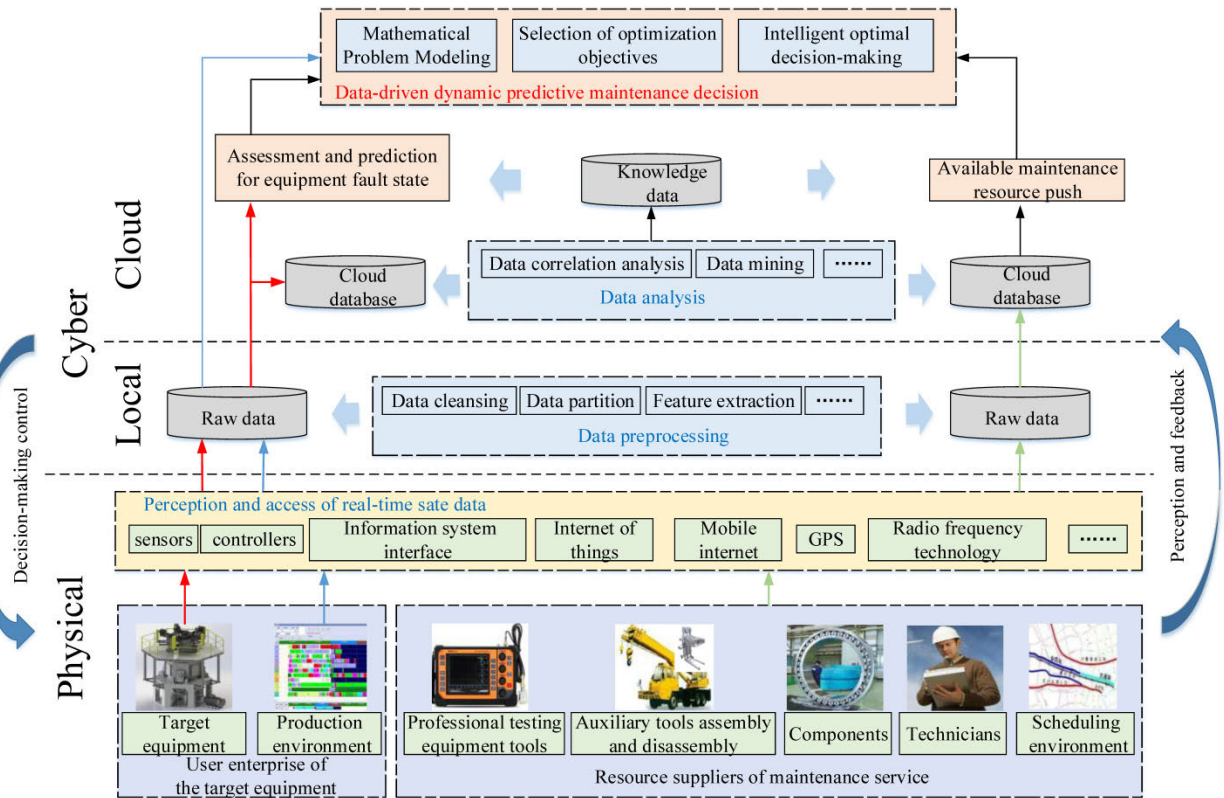


FIGURE 1. The structural framework of information sharing and service network for predictive maintenance.

this layer include data cleansing technology, data partition technology, and feature extraction technology. This data processing for each target object is completed independently by their owner. After preprocessing, these filtered data are uploaded to the cloud function layer of the cyberspace.

C. CLOUD FUNCTION LAYER OF THE CYBERSPACE

Related state feature parameters are extracted from the filtered data through data analysis and mining technologies in this layer. It is necessary to extract different state feature parameters for different data sources. For predictive maintenance target equipment, the extractable state parameters include fault state indexes, the degradation state indexes of production efficiency, the stability state indexes of process quality, remaining service life indexes, etc. For the production environment of target equipment, related production task information for a specific period time and their relative importance should be extracted. For maintenance service tools and device resources, the extractable state parameters include spatial location, available quantity, functional state, scheduling cost, scheduling time, etc. For consumption category maintenance resources like maintenance service spare parts, the extractable state parameters include attribution state, spatial location, available quantity, scheduling time, scheduling cost, functional state, etc. For maintenance service technicians, the extractable state parameters include

attribution state, spatial location, available quantity, scheduling time, scheduling cost, skill state, etc.

Based on these data, fault state prediction information of target equipment is obtained based on corresponding equipment fault diagnosis and prediction technologies, available maintenance resource collection is pushed in time, and then predictive maintenance decisions can be supported. Moreover, these state information of different objects related to predictive maintenance services are integrated and stored in a could database. Self-comparison capabilities among the same or similar equipment objects are provided to aid in object performance evaluation and state prediction [30], [31]. Based on the state information of these same or similar service resource objects which is collected and uploaded by different service suppliers, the available service resource objects range for complex equipment maintenance is expanded.

III. INTEGRATED INTELLIGENT GREEN SCHEDULING OPTIMIZATION STRATEGY FOR COMPLEX EQUIPMENT

A. MATHEMATICAL PROBLEM MODELING FOR PREDICTIVE MAINTENANCE DECISION

Based on the framework proposed above, associated knowledge data come from real-time fault state of target equipment, the working environment of target equipment and scheduling environment of service resources can be obtained timely to support predictive maintenance decisions. In this

section, both the economic performance and the environmental performance are concerned, an integrated mathematical model for predictive maintenance decision is established to minimize maintenance cost and the carbon emissions of maintenance scheduling process simultaneously. The final decision result includes the maintenance time node and the corresponding optimal scheduling scheme of maintenance resources.

1) MODEL DESCRIPTION AND PARAMETER DEFINITION

Some illustrations of this mathematical model are described below.

- A target complex equipment may occur several different fault types during its entire life cycle. Different maintenance service tasks can be combined to make a synthetic maintenance plan under certain conditions [17], [32]. This paper only discusses the predictive maintenance decision of a single fault type. A fault type is divided into several fault levels according to the fault degree and several feasible maintenance modes are distinguished. The applicability and expected service execution time of different maintenance modes are different for different fault levels. Different maintenance modes under different fault levels will result in different equipment improvements. Its effects will be reflected in the extension of equipment life and the restoration of equipment state. Some models for the equipment fault probability have been provided [17], [33]. The equipment fault probability for a specific time node can be calculated.
- Based on existing scheduling information and historical experience information, the job task sequence associated with the maintenance target equipment between the scheduling decision time node and the expected equipment fault time node can be obtained by the user enterprise. Each job task is uninterrupted and maintenance service can only be performed between two adjacent job tasks. The importance of different job tasks is distinguished. The delay in job tasks caused by maintenance will lead to the delay penalty cost.
- Predictive maintenance is beneficial to improve the production efficiency and the overall product quality. The probability of defective products can also be reduced. These improvements and the flexible manufacture ability of user enterprises can offset part of the delay penalty cost. The equipment reliability will gradually decrease and the equipment maintenance cost will present a concave curve with the degradation of the device equipment state. Considering the degradation mode and the coupling relationship of complex functional structures, to restore the equipment state through the maintenance service in the early stage of equipment performance degradation can create more service revenue.
- Monitoring and forecasting of the target equipment fault state can help to obtain more explicit requirements of type and quantity for maintenance service resources. The service resource type includes spare parts,

professional equipment tools, and technicians. There have demand relationships between maintenance modes and needed resource types. Based on the framework proposed above, not only the schedulable scope of maintenance resources is extended, but also more real-time and accurate maintenance service resource state information can be obtained. Each resource type has several different feasible scheduling paths which correspond to different scheduling time and cost.

To describe the decision problem of predictive maintenance clearly, some related parameters are defined in Table 1.

2) OBJECTIVE FUNCTION FOR PREDICTIVE MAINTENANCE DECISION

There are two different optimization objectives are proposed in this mathematical model. The first optimization objective attempts to minimize a global maintenance cost results from resource consumption, production delay, and fault risk, etc. The second optimization objective seeks to minimize the carbon emission during maintenance resource scheduling.

The direct maintenance cost and the system fault risk cost are usually considered as common optimization objectives [34]. However, maintenance service revenue is neglected. After the maintenance service, the equipment trouble-free running time is extended and the production efficiency is improved. There is a nonlinear relation between maintenance cost and maintenance revenue under the complex and polytropic manufacturing environment. Therefore, the more precise predictive maintenance plan should simultaneously emphasize the direct maintenance cost, the risk cost, and the maintenance service revenue. A global maintenance cost is proposed in this section. This global cost is divided into four parts, resource scheduling cost, delay cost of job tasks, maintenance service economic benefits, and system cumulative fault risk cost.

The resource scheduling cost includes the scheduling cost of various service resources such as professional tools, technicians and spare parts. The scheduling cost CR is defined as:

$$CR = \sum_{i=1}^b \sum_{j=1}^h \sum_{k=1}^{MK} (m_i \times O_{ij} \times Se_{jk} \times C_{jk}) \quad (1)$$

The execution of the maintenance plan at different time node will cause the delay of subsequent job tasks. The delay cost CD is defined as:

$$CD = \sum_{i=1}^b \sum_{j=1}^l \sum_{k=1}^n (Td + m_i \times st_j \times Ts_{ij}) \times Cp_k \times Rev_{ijk} \quad (2)$$

where

$$Td = \frac{(Tz - Tp) + |(Tz - Tp)|}{2} \quad (3)$$

$$Tz = \max_{\substack{i=1,2,\dots,b \\ j=1,2,\dots,h \\ k=1,2,\dots,MK}} (m_i \times O_{ij} \times Se_{jk} \times T_{jk}) \quad (4)$$

$$Rev_{ijk} = (w_k \times Re_k \times Rc_{ij} \times m_i \times st_j) \quad (5)$$

TABLE 1. Parameters description.

Parameter	Description
l	Total number of fault levels
b	Total number of maintenance modes
m_i	Judgement parameter of the i -th maintenance mode which takes the value 0 or 1
st_i	Judgement parameter of the i -th fault level which takes the value 0 or 1
Ts_{ij}	Expected execution time of the i -th maintenance mode for the j -th fault level
h	Total number of maintenance resources types related to a certain fault maintenance
MK	Maximum number of feasible scheduling paths, $MK = \max(k_1, k_2, \dots, k_i)$, k_i denotes the total number of feasible scheduling paths for the i -th resource type.
O_{ij}	Demand judgment parameter of the j -th resource for the i -th maintenance mode which takes the value 0 or 1
T_{ij}	Scheduling time of the j -th path for the i -th resource
C_{ij}	Scheduling cost of the j -th path for the i -th resource
Se_{ij}	Judgement parameter of the j -th path for the i -th resource which takes the value 0 or 1
Tz	Total resource scheduling time of a certain predictive maintenance service plan
TP	Time difference between decision-making time node and corresponding expected execution time node of maintenance service.
TL	Maintenance service time after the equipment shutdown fault
Cl	The penalty cost of unit time after the equipment shutdown fault
n	Total number of job tasks associated with the maintenance target equipment
Tt_i	Expected execution time of the i -th job task
w_i	Relative importance of the i -th job task
Pl_i	Probability of equipment fault before the execution time node of the i -th job task
Cp_i	Delay penalty cost of unit time for the i -th job task
Cr_i	Expected fault level during the execution of the i -th job task
Ex_i	Judgment parameter for performing maintenance service before the i -th job task which takes the value 0 or 1
In_{aver}	Average revenue of unit time generated by maintenance target equipment
In_{amp}	Increased revenue of unit time after maintenance service
Til_{ij}	Increased equipment life after the j -th maintenance mode is adopted in the i -th fault level
Rc_{ij}	Reduction factor of job task time after the i -th maintenance mode is adopted in the j -th fault level
Re_i	Correction factor of penalty cost for the i -th job task
Xz_i	Correction factor of unit time service revenue when maintenance service is performed before the execution time node of the i -th job task
a_i	Relative weight of the i -th maintenance cost part
Rg	Carbon conversion coefficient of gasoline
Re	Carbon conversion coefficient of electricity
Gs_{jk}	Total fuel consumption of the k -th path for the j -th resource type
p_j	Judgement parameter of energy consumption for the j -th resource that takes the value 0 or 1
Pm_{jk}	Average power of the k -th path for the j -th resource type

The increased equipment trouble-free running time, the restoration for the level of qualified product rate and the improvement of production efficiency will bring additional economic benefits to user enterprises. The maintenance service economic benefits IF is defined as:

$$IF = \sum_{i=1}^b \sum_{j=1}^l \sum_{k=1}^n Xz_k \times Ex_k \times (In_{aver} + In_{amp}) \times Til_{ij} \times m_i \times st_j \tag{6}$$

The equipment state change is uncertain. It is necessary to consider the equipment fault risk cost when making maintenance decisions. The system cumulative fault risk cost FR is defined as:

$$FR = \sum_{i=1}^n (In_{aver} + Cl) \times Tl \times Pl_i \times Ex_i \tag{7}$$

where

$$Tl = \max_{\substack{i=b \\ j=1,2,\dots,h \\ k=1,2,\dots,MK}} (m_i \times O_{ij} \times Se_{jk} \times T_{jk}) + Ts_{bl} \tag{8}$$

The cost IF should be increased, while the cost CR , CD , and FR should be reduced. User enterprises may pay different attention to these four parts. This paper combines these four cost parts into a global maintenance cost by weighting. Thus, the optimization objective for the maintenance cost is defined as follows:

$$\begin{aligned} &\min (a_1 \times CR + a_2 \times CD + a_4 \times FR - a_3 \times IF) \\ &\text{s.t.} \begin{cases} \sum_{i=1}^b m_i = 1 \\ \sum_{i=1}^l st_i = 1 \\ \sum_{i=1}^n Ex_i = 1 \end{cases} \end{aligned} \tag{9}$$

where the vector $a = (a_1, a_2, a_3, a_4)$ denotes the weight distribution of four cost parts with $\sum_{i=1}^4 a_i = 1$. Their value can be confirmed by user enterprises through expert estimation and comprehensive assessment.

Two carbon emission sources of the predictive maintenance service process are included in this optimization objective for the environmental impacts.

The first source are carbon emissions come from the maintenance resource distribution process. The corresponding maintenance service resource scheduling becomes very complicated since complex equipment involves multidisciplinary technologies and various types of components from different sources [5], [35]. Different operation links (for example, disassembly, inspection, maintenance, assembly, etc.) need to depend on different maintenance resources (such as professional testing equipment, hoisting tools, assembly tools, professional operators, etc.) during the process of maintenance

service. These maintenance resources may belong to different maintenance service resources suppliers of different spatial distribution. From the perspective of environmental protection, different distribution methods and routes will produce different fuel consumption or carbon emissions. The carbon emissions CE_{rd} caused by fuel consumption can be calculated as:

$$CE_{rd} = Rg \times \sum_{i=1}^b \sum_{j=1}^h \sum_{k=1}^{MK} (m_i \times O_{ij} \times Se_{jk} \times Gs_{jk}) \quad (10)$$

The carbon conversion coefficient of different common energy resources can be obtained by converting the current coefficient of standard coal equivalent [36], [37]. The carbon conversion coefficient Re of the electricity is 0.781 kg/kwh and the carbon conversion coefficient Rg of gasoline is 2.26 kg/L [38]. Fuel consumption of the distribution process is related to vehicle type, driving speed, vehicle weight, load, and distance [39]. Based on the existing research [40], the total fuel consumption Gs_{jk} of the k -th path for the j -th resource type is expressed as:

$$Gs_{jk} = (Fr_{jk} \times L_{jk} + Fv_{jk} \times Vm_{jk}) \times D_{jk} \quad (11)$$

where Fr_{jk} denotes fuel consumption constant of the k -th path, Fv_{jk} is fuel consumption constant of the corresponding distribution vehicles, L_{jk} equals to the sum of no-load weight of distribution vehicle and vehicle load, Vm_{jk} is the average velocity of distribution vehicle, and D_{jk} is the distribution distance of the k -th path.

The second source are carbon emissions come from the maintaining operation process. Maintenance resource tools with different types and states generate different unit energy consumption. The carbon emissions CE_{mo} caused by electricity consumption during maintenance service can be calculated as:

$$CE_{mo} = Re \times \sum_{i=1}^b \sum_{j=1}^h \sum_{k=1}^{MK} \sum_{l=1}^l (m_i \times O_{ij} \times Se_{jk} \times Pm_{jk} \times p_j \times Tsig) \quad (12)$$

The optimization objective for environmental impacts is to reduce the total carbon emissions of maintenance service. Therefore, the optimization objective for environmental impacts is defined as follows:

$$\min (CE_{rd} + CE_{mo}) \quad (13)$$

B. INTELLIGENT OPTIMIZATION ALGORITHM

As a hot research direction, researchers constantly contribute new optimization algorithms, analyze algorithm performance and improve existing algorithms. For example, Zhao et al. proposed a modified cuckoo search algorithm with a self-adaptive step size, some neighbor-study strategies and an improved lambda iteration strategy [41]. Zhu et al. improved the convergence rate and the global optimization ability of the dandelion algorithm by adopting probability-based mutation [42]. Li et al. put forward a novel formula of

characterizing robustness for algorithms of learning to rank and proposed an R²Rank approach [43], and Wang et al. presented a hybrid algorithm, namely HICATS, combining discrete imperialist competition algorithm and tabu search [44]. Function optimization problems of the manufacturing field have been typical application goals for these intelligent optimization algorithms [45]. The existing research provides a good reference for solving the function optimization problem proposed in this paper.

In the model of optimization problem established above, a feasible predictive maintenance service scheduling scheme includes the maintenance time node, the maintenance mode and the corresponding optimal allocation scheme of maintenance resources. The time interval between the scheduling decision time node and the expected equipment fault time node is relatively long in a normal condition. The variable n that is the total number of job tasks associated with the predictive maintenance target equipment in this time interval may take a relatively large integer value. The variable b that is the total number of fault maintenance modes may take a relatively large integer value under the method of detailed partition. The multisupplier collaboration based maintenance service mode extends the schedulable scope of maintenance resources. The variable k_i that is the number of feasible scheduling paths for the i -th resource type may take a relatively large integer value, too. Therefore, predictive maintenance service scheduling for the complex equipment under the ubiquitous state data awareness environment is a complicated scheduling problem, the number of possible predictive maintenance service scheduling schemes is $\prod_{i=1}^h n \times b \times k_i$, and this number is enormous. For the complex scheduling problem, when the number of possible scheduling schemes becomes very large, the efficiency of traditional calculation methods drops considerably, and thus, the actual application cannot be satisfied. The heuristic algorithm can be an appropriate method for addressing this problem since it can find a feasible solution in an acceptable time compared with the traditional optimal solution algorithms [46].

The proposed optimization problem of predictive maintenance has two objectives. There are interactions between different objectives in a multiobjective optimization problem, and the improvement of an objective may cause the performance reduction of the other objectives. To solve different multiobjective optimization models of specific engineering problems, various of multiobjective optimization algorithms have been proposed and utilized by researchers. For example, Guo et al. considered multiobjective optimization problems of the product disassembly planning with resource-constrained and sequence-dependent relationship and proposed a lexicographic multiobjective scatter search method [47], [48]. Li et al. proposed a multiobjective optimization configuration method for maintenance service resources of complex equipment based on an improved NSGA-II algorithm [46]. Other classic algorithms include PESA, SPEA2, etc [49], [50]. Among them, NSGA-II shows better convergence stability and faster convergence rate for

the optimization problem with less than three objectives [46], [51]–[53]. In addition, an optimization problem with a similar type was solved successfully by utilizing NSGA-II [46]. Hence, this paper solves the proposed two-objective optimization problem based on the improved NSGA-II.

The final optimization result is a set of Pareto optimal solutions. As the Pareto front of feasible solution space, there has a non-dominating relationship between any two different solutions of this set. Then, from the point of practical control requirements of enterprise for the maintenance cost and the carbon emission index, a proper solution can be chosen to guide the final predictive maintenance plan that can be motivated by the results in discrete event systems [54]–[56]. The flowchart of NSGA-II is shown in Fig. 2.

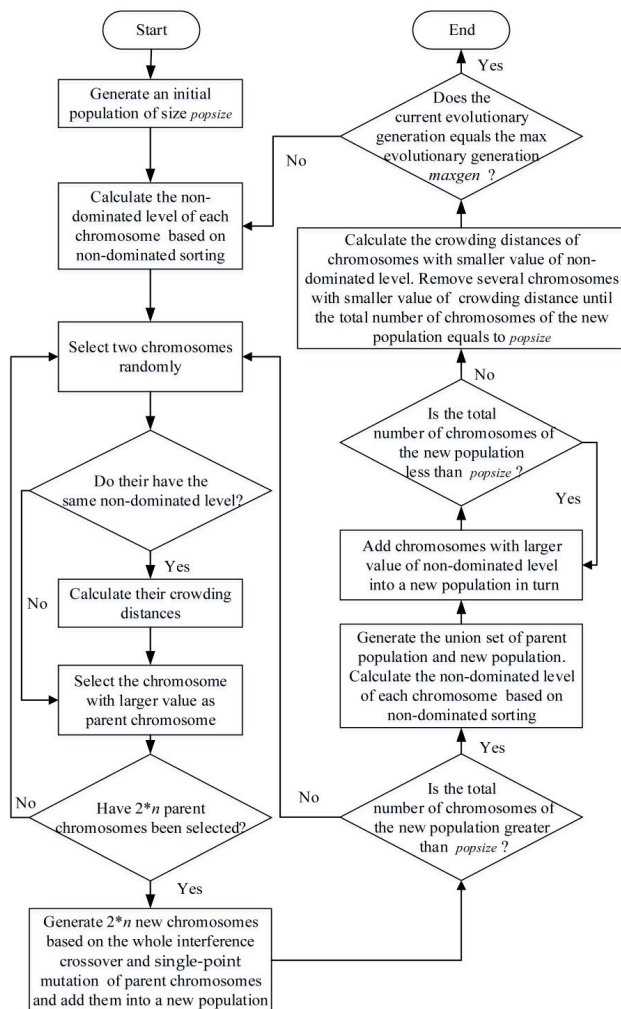


FIGURE 2. The flowchart of improved NSGA-II.

1) CHROMOSOME CODING METHOD FOR MAINTENANCE PLANS

The coding structure of a feasible predictive maintenance plan is shown in Fig. 3. The maintenance plan chromosome is coded with integer. It consists of three parts, the execution time node, the maintenance mode, and the corresponding

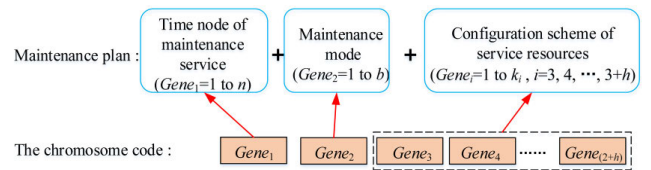


FIGURE 3. The structure of chromosome code for predictive maintenance service plan.

maintenance service resource allocation scheme. The code length of a chromosome is $2+h$. The $Gene_1$ and $Gene_2$ of chromosome code denote the selected execution time node of maintenance service and the type of selected maintenance mode, respectively. Namely, this service plan would be executed before the a -th job task when $Gene_1 = a$, the b -th maintenance mode type is selected when $Gene_2 = b$. The selected scheduling paths for corresponding h types of service resources are represented through $Gene_3$ to $Gene_{2+h}$. When $Gene_i = c$, it indicates the c -th path of the i -th resource type is selected. Corresponding chromosome code of a feasible maintenance plan code can be obtained through the conversion and extraction of mathematical model parameters.

2) THE CROSSOVER AND MUTATION METHOD

As shown in Fig. 4, a small-scale whole interference crossover method is used to assist in enhancing population diversity and global search capabilities. Judgment of single-point mutation is carried out for each chromosome after the whole interference crossover process.

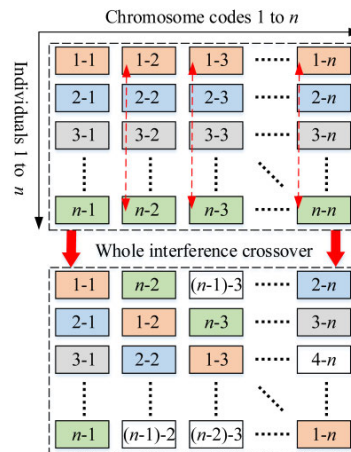


FIGURE 4. The process of whole interference crossover.

3) THE NON-DOMINANT SORTING METHOD

Assume that there are M optimization objectives. We use $f_k(B)$ and $f_k(C)$ to denote the calculated value of the k -th optimization objective for feasible maintenance plans B and C, respectively. When $f_i(B) \leq f_i(C)$ is met for arbitrary i ($i = 1, 2, \dots, M$) and there exists j ($j \in \{1, 2, \dots, M\}$) such that $f_j(B) < f_j(C)$ comes into existence, the maintenance plan C

is dominated by maintenance plan B. When there exist i ($i \in \{1, 2, \dots, M\}$) and j ($j \in \{1, 2, \dots, M\}$) such that $f_i(B) < f_i(C)$ and $f_j(B) > f_j(C)$ come into existence, respectively, there exists a non-dominated relationship between B and C. The non-dominated sorting method is shown in Fig. 5.

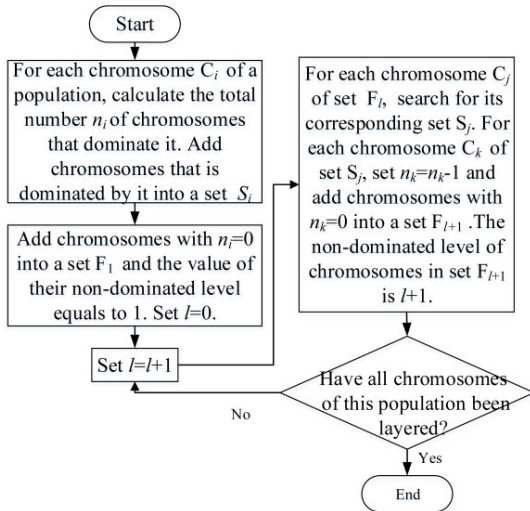


FIGURE 5. The process of non-dominant sorting.

4) CALCULATION OF THE CROWDING DISTANCE

When several chromosomes with the same chromosome non-dominated level should be to be compared, the calculation of crowding distance is utilized to distinguish them and maintain the diversity of the individual population. Fig. 6 shows the calculation process of the crowding distance.

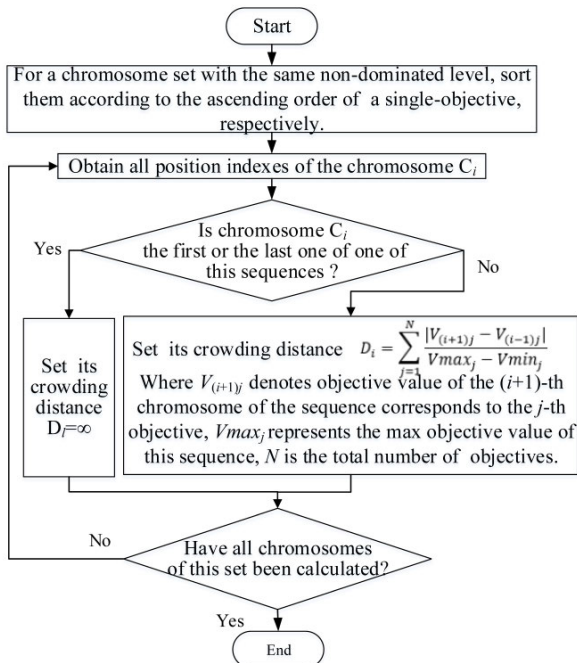


FIGURE 6. Calculation process of the crowding distance.

C. DATA-DRIVEN DYNAMIC ADJUSTMENT STRATEGY

Things are constantly changing and full of uncertainties. In addition to the accuracy of prediction information for fault state of target equipment, dynamic characteristics of maintenance service decision environment should also be concerned. There may be unexpected state changes for related service resources, such as changes in scheduling time or cost. In order to adapt to external environment pressures (such as the increasingly fierce market competition, customers individualized demands, environmental protection requirements, etc.), more flexible and dynamic production scheduling mode may lead to frequent changes of job task sequence associated with target equipment, constraint conditions and optimization objectives of maintenance decision may also be adjusted according to the subjective desire of enterprise.

To improve the responsiveness of predictive maintenance decision-making to uncertain factors, a data-driven dynamic maintenance decision strategy is adopted in this section. This dynamic decision process for an unexecuted maintenance plan is described as follows. Assume that a corresponding maintenance plan for a maintenance task is determined at time t_i . The $T_s(t_i)$ and $T_E(t_i)$ denote respectively the expected maintenance execution time node and expected termination time node of dynamic correction process that is calculated at time t_i . When $t_{i+1} \leq T_E(t_i)$ is satisfied and the $(i + 1)$ -th dynamic adjustment operation is triggered, rescheduling calculation which based on the latest data for this unexecuted maintenance task will be performed at t_{i+1} and then the original maintenance plan will be updated. The updated content of maintenance plans includes three parts, the execution time node, the maintenance mode which affects the maintenance resource requirement, and the configuration scheme of corresponding maintenance service resources. The resource configuration scheme includes different resource types and corresponding suppliers.

We do not restrict the driving and termination conditions for dynamic adjustment operations for an unexecuted maintenance plan and set it flexibly. Feasible driving conditions include the error threshold of prediction accuracy for fault index, the change of production plan, the state change of service resources and the maintenance service environment, the adjustment of optimization objectives for the maintenance plan, etc. The time node which satisfies the max scheduling time of necessary maintenance resources before the execution time node can be one of the feasible termination conditions.

IV. CASE STUDY

The large vertical mill with the complex product structure and a long lifecycle is the key equipment of the cement production system. The grinding roll is one of the key parts and the bearing is its core component. To guarantee the operation performance of vertical mills, working status monitoring of the bearing has been implemented in some enterprises. In this section, relevant monitoring and prediction data of bearing fault state, common maintenance mode data and available

maintenance resource data which come from a user enterprise of the large vertical mill equipment are collected as the case data. The objective is to validate and analyze the impact of the proposed integrated intelligent green scheduling optimization method on predictive maintenance decisions.

A. PREPARATION OF THE CASE DATA

In this case, a predictive maintenance requirement is generated when the bearing fault state indicator of the target equipment reaches its critical threshold in this case. The corresponding bearing fault state that beyond this critical threshold are divided into five levels. There are three different maintenance modes to be chosen which include the simple non-replacement maintenance action (e.g., cleaning, lubrication, etc.), the complex non-replacement maintenance action (e.g., the repair of damaged parts) and the replacement maintenance action. Different maintenance modes can be implemented to deal with the same fault state. A total of ten maintenance service resource types are needed to support maintenance operations under different maintenance modes. From the generation of maintenance requirements to the final implementation of maintenance service, there are 24 job tasks associated with the target equipment in the acquisition interval of case data.

The initial fault state monitoring and prediction data of the generation time node of maintenance requirement and other relevant parameter data are shown in Table 2. The corresponding parameter definitions are shown in Table 1 of section 3. The data has been preprocessed to eliminate the impact of dimension and order of magnitude. The corresponding initial predictive maintenance plan can be obtained based on them.

The real-time state of relevant target objects is changing constantly under the dynamic maintenance service environment. Considering the uninterruptible assumption of the job task, the latest relevant data of the completion time node for each job task are all collected. These related data include the monitoring and prediction data of bearing fault state and the state data of available maintenance resources. They will be used to analyze the impact of the data-driven dynamic adjustment strategy on predictive maintenance decisions. Other parameters such as job task sequence and its weight do not change with time in this case.

These dynamically changing parameters include the equipment fault probability vector Pl , the corresponding fault level vector Cr , the correction factor vector Rt of the resource scheduling time, the service resources scheduling time matrix T_{hxMK} , the service resources scheduling cost matrix C_{hxMK} , and fuel consumption matrix G_{shxMK} . Due to a large amount of data, the changes of vector Pl and vector Cr are shown in Figs. 7(a) and 7(b), respectively. Data change of the matrix T_{hxMK} , G_{shxMK} and C_{hxMK} are not listed.

B. COMPARISON AND ANALYSIS

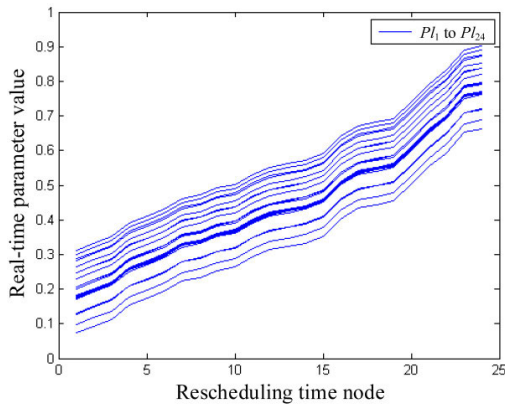
The case data in Table 2 is utilized to test the effectiveness and superiority of the proposed improved NSGA-II in solving the

TABLE 2. Parameters and values.

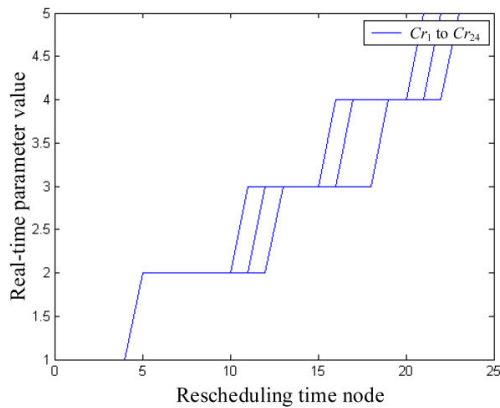
Parameter name	Parameter value
m_{aver}	5
m_{amp}	2
Cl	8
Pl	[0.3, 0.32, 0.34, 0.38, 0.40, 0.42, 0.45, 0.46, 0.48, 0.49, 0.52, 0.54, 0.55, 0.56, 0.58, 0.63, 0.66, 0.67, 0.68, 0.73, 0.78, 0.82, 0.88, 0.89]
w	[0.4, 0.5, 0.5, 0.7, 0.3, 0.5, 0.6, 0.4, 0.6, 0.3, 0.4, 0.5, 0.5, 0.4, 0.7, 0.3, 0.2, 0.5, 0.3, 0.4, 0.7, 0.2, 0.6, 0.7]
Cp	[2, 3, 3, 4, 1, 2, 3, 2, 3, 1, 2, 2, 3, 2, 4, 3, 2, 1, 4, 3, 4, 2, 2, 3]
Re	[0.82, 0.90, 0.75, 0.79, 0.83, 0.85, 0.75, 0.90, 0.65, 0.65, 0.55, 0.60, 0.72, 0.80, 0.75, 0.73, 0.73, 0.85, 0.76, 0.80, 0.75, 0.65, 0.65, 0.90]
Tt	[2.7, 3.0, 2.2, 1.5, 4.2, 2.1, 3.2, 1.9, 4.5, 6.0, 5.2, 2.8, 1.3, 3.5, 3.8, 2.4, 1.8, 3.5, 2.6, 2.8, 3.5, 2.5, 1.6, 2.9]
Xz	[1.00, 0.97, 0.95, 0.94, 0.89, 0.85, 0.83, 0.78, 0.73, 0.68, 0.61, 0.57, 0.54, 0.52, 0.49, 0.47, 0.46, 0.45, 0.44, 0.40, 0.37, 0.34, 0.32, 0.30]
a	[0.25, 0.40, 0.20, 0.15]
Cr	[1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 5, 5]
O_{bxh}	$\begin{bmatrix} 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 \end{bmatrix}$
T_{sbxt}	$\begin{bmatrix} 0.5 & 0.6 & 0.9 & 999 & 999 \\ 0.8 & 0.9 & 1.1 & 1.4 & 999 \\ 1.2 & 1.4 & 1.6 & 1.8 & 2.3 \end{bmatrix}$
Til_{bxt}	$\begin{bmatrix} 2 & 4 & 5 & 0 & 0 \\ 3 & 6 & 9 & 10 & 0 \\ 5 & 9 & 13 & 19 & 23 \end{bmatrix}$
Rc_{bxt}	$\begin{bmatrix} 0.98 & 0.92 & 0.85 & 1 & 1 \\ 0.94 & 0.88 & 0.80 & 0.80 & 1 \\ 0.92 & 0.84 & 0.76 & 0.73 & 0.70 \end{bmatrix}$
T_{hxMK}	$\begin{bmatrix} 2.1 & 1.8 & 1.2 & 2.9 & 3.2 & 2.8 & 1.0 & 999 \\ 3.2 & 2.4 & 3.5 & 1.9 & 4.2 & 2.8 & 3.6 & 999 \\ 1.3 & 2.9 & 2.2 & 1.4 & 2.3 & 3.9 & 2.7 & 1.8 \\ 5.2 & 3.8 & 6.0 & 3.2 & 3.5 & 4.8 & 4.0 & 3.2 \\ 3.3 & 2.2 & 2.0 & 3.7 & 4.2 & 2.8 & 999 & 999 \\ 7.2 & 5.3 & 4.1 & 6.8 & 6.3 & 3.9 & 4.8 & 999 \\ 4.2 & 2.7 & 5.2 & 3.9 & 4.8 & 5.7 & 3.8 & 999 \\ 2.3 & 3.9 & 2.2 & 1.4 & 3.3 & 4.6 & 2.8 & 1.9 \\ 5.4 & 3.1 & 2.9 & 2.4 & 6.1 & 4.3 & 2.6 & 3.7 \\ 3.3 & 2.8 & 4.6 & 5.2 & 3.6 & 2.2 & 4.1 & 999 \end{bmatrix}$
C_{hxMK}	$\begin{bmatrix} 22 & 32 & 24 & 28 & 24 & 18 & 29 & 999 \\ 16 & 18 & 13 & 23 & 28 & 20 & 30 & 999 \\ 22 & 16 & 28 & 20 & 28 & 22 & 27 & 32 \\ 25 & 37 & 28 & 18 & 25 & 40 & 35 & 27 \\ 32 & 38 & 35 & 36 & 43 & 36 & 999 & 999 \\ 22 & 37 & 33 & 27 & 29 & 41 & 32 & 999 \\ 36 & 48 & 31 & 42 & 33 & 38 & 41 & 999 \\ 22 & 18 & 25 & 19 & 25 & 50 & 31 & 27 \\ 25 & 20 & 24 & 26 & 34 & 23 & 24 & 22 \\ 27 & 38 & 32 & 39 & 29 & 35 & 29 & 999 \end{bmatrix}$
G_{shxMK}	$\begin{bmatrix} 2 & 4 & 5 & 2 & 6 & 8 & 10 & 999 \\ 6 & 8 & 5 & 7 & 12 & 10 & 13 & 999 \\ 33 & 28 & 36 & 30 & 23 & 26 & 27 & 31 \\ 15 & 17 & 18 & 21 & 25 & 20 & 15 & 17 \\ 12 & 8 & 15 & 6 & 13 & 16 & 999 & 999 \\ 17 & 22 & 13 & 27 & 19 & 14 & 13 & 999 \\ 16 & 18 & 21 & 24 & 23 & 18 & 21 & 999 \\ 12 & 10 & 15 & 9 & 12 & 10 & 11 & 17 \\ 24 & 20 & 28 & 16 & 30 & 17 & 26 & 32 \\ 17 & 18 & 22 & 19 & 19 & 15 & 24 & 999 \end{bmatrix}$

TABLE 2. (Continued.) Parameters and values.

Pm_{hsMK}	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0
	85	94	106	79	88	92	72	102
	8	12	6	15	18	8	12	9
	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0
	5	7	14	8	12	18	7	999
	10	18	25	16	12	15	23	17
	23	17	24	16	30	26	34	22
	12	18	22	19	12	15	24	999
p_h	[0, 0, 1, 1, 0, 0, 1, 1, 1, 1]							



(a)



(b)

FIGURE 7. Dynamic environment data. (a) Variation of parameter values in vector Pf . (b) Variation of parameter values in vector Cr .

integrated intelligent green scheduling problem. For comparison, the NSGA-II proposed in [46] is also used. The same encoding method and decoding rules are used to have a fair comparison. These algorithms run on Intel I5 (3.20 GHz/8.0G RAM) PC with a Windows 10 operating system. In order to obtain a suitable parameter combination of the improved NSGA-II and compare the performance of the two algorithms, we have conducted some preliminary experiments with different parameter combinations. The experimental set of the initial population is {50, 100, 200, 350, 500}. The experimental set of the maximum evolutionary generation is {50, 100, 200, 350}. The experimental set of the crossover

probability is {0.85, 0.9, 0.95}. The experimental set of the mutation probability is {0.05, 0.1, 0.15}. The results of multiple optimization calculations show that both algorithms can effectively solve the integrated intelligent green scheduling problem. However, under the same parameter conditions, the average run time of the proposed NSGA-II in this paper is reduced by approximately 8% compared with the algorithm in [46]. The improvement of algorithm efficiency has important significance for timely maintenance decision. When both the size of initial population and the maximum evolutionary generation are small, for example, both are 50, the Pareto front of the proposed algorithm contains better solutions compared with the algorithm in [46]. When both the size of initial population and the maximum evolutionary generation are large enough, for example, both are 350, the Pareto optimal front of the case problem can be found by these two algorithms. Nevertheless, the probability of falling into the local optimal solution of the proposed algorithm is greatly reduced. Besides, the time complexity of the improved NSGA-II is $O(maxgen*obn*popsize^2)$. The maximum evolutionary generation $maxgen$, the number of objectives obn and the population size $popsize$ are the key influencing factors of the algorithm performance. The adopted whole interference crossover method of this improved NSGA-II can effectively reduce the value of $maxgen$ and $popsize$ while improving the optimization speed.

Based on experiments and analysis, an optimal combination of algorithm parameters with better performance is selected.

The selected algorithm parameters are as follows: the size of the initial population is 100; the maximum evolutionary generation is 100; the crossover probability is 0.9; the mutation probability is 0.1. The detailed influence of parameters on the optimization quality and the further analysis of the relationship between the problem size and algorithm parameters will be discussed in future work.

The case problem is solved by the improved NSGA-II. Fig. 8(a) shows the proportion change process of non-inferior solutions. Fitness change of two different optimization objectives are shown in Figs. 8(b) and 8(c), respectively. Fig. 8(d) shows the final Pareto front.

Several feasible predictive maintenance plans come from the final Pareto optimal solution set are listed in Table 3. To build a benchmark, an optimal maintenance plan which considering the single maintenance cost objective is obtained based on the general single objective genetic algorithm and its corresponding carbon emission is calculated. The optimal cost fitness is 26.861536, a feasible maintenance plan chromosome is [5, 1, 6, 3, 8, 2, 1, 6, 2, 2, 8, 6], and the corresponding carbon emission fitness is 133.9262. Based on theoretical analysis, this solution should be dominated or included in the Pareto front. As verified in Fig. 8(d), this single objective optimization result is included in the Pareto front for the optimization problem. The Pareto front solution set also includes some more balanced feasible predictive maintenance plans. Compared with the single objective optimization which only

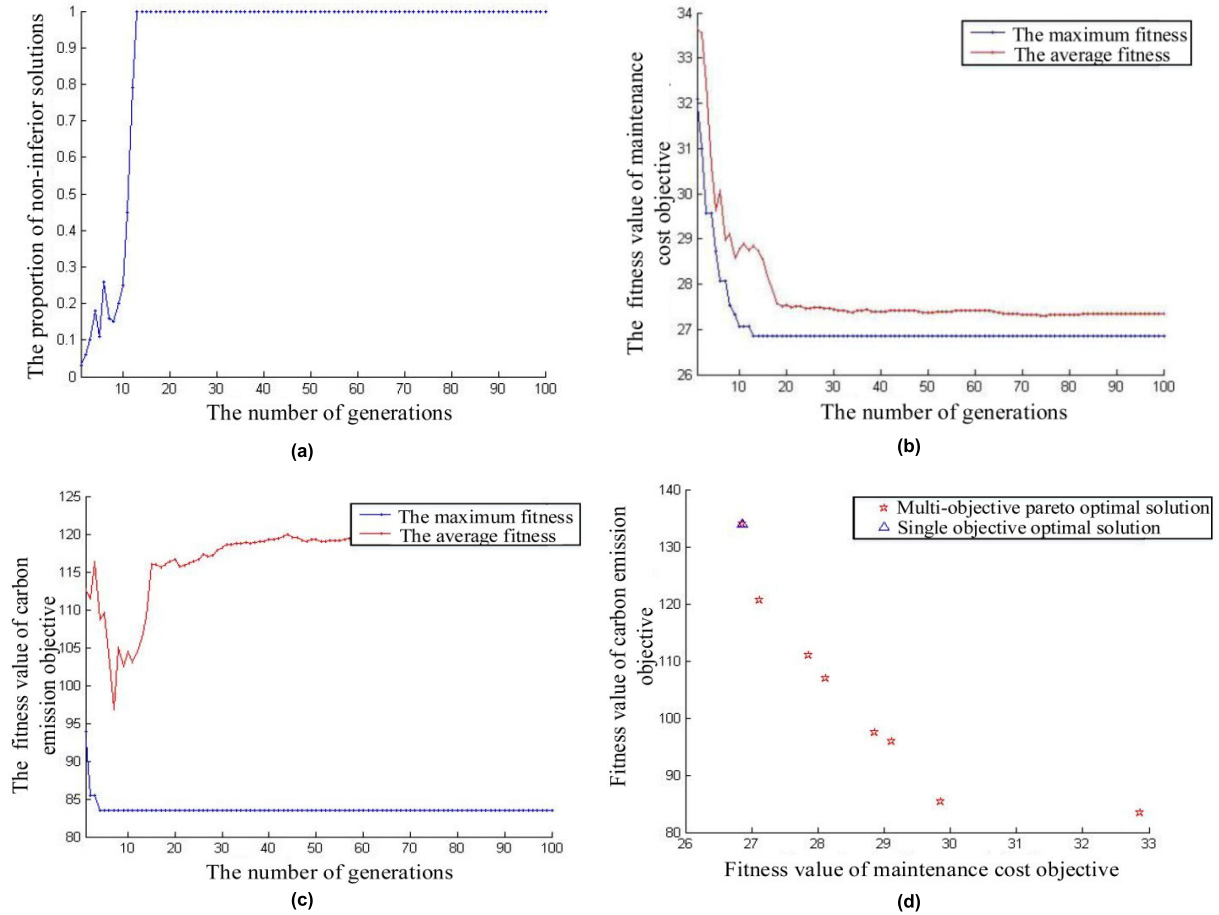


FIGURE 8. Optimization process based on improved NSGA-II. (a) Proportion change process of non-inferior solutions. (b) Fitness change of the maintenance cost objective. (c) Fitness change of the carbon emission objective. (d) Pareto front of the 100th generation.

TABLE 3. Typical optimal maintenance plans of the Pareto front solution set.

Maintenance plan chromosome	Maintenance cost fitness value	Carbon emission fitness value
[5, 1, 1, 4, 8, 4, 2, 6, 7, 1, 8, 6]	32.86	83.50
[5, 1, 1, 3, 8, 8, 4, 6, 7, 1, 8, 6]	29.86	85.40
[5, 1, 1, 3, 8, 8, 4, 6, 7, 4, 8, 6]	29.11	95.96
[5, 1, 1, 3, 8, 8, 1, 6, 7, 1, 8, 6]	28.86	97.40
[5, 1, 1, 3, 8, 8, 1, 6, 7, 4, 8, 6]	28.11	107.02
[5, 1, 6, 3, 8, 8, 1, 6, 7, 1, 8, 6]	27.86	110.96
[5, 1, 6, 3, 8, 8, 1, 6, 7, 4, 8, 6]	27.11	120.58
[5, 1, 6, 3, 8, 8, 1, 6, 7, 2, 8, 6]	26.86	133.93

considering maintenance cost, multiobjective optimization for predictive maintenance decision enables user enterprise to minimize carbon emissions of maintenance process while controlling the maintenance cost.

The detailed maintenance plan information represented by chromosome code can be obtained by decoding. For a feasible maintenance plan chromosome [5, 1, 1, 3, 8, 8, 1, 6, 7, 1, 8, 6], the first code 5 represents that maintenance service

should be executed before the fifth job task. The second code 1 indicates that the first maintenance mode should be adopted. The remaining code string represents the necessary maintenance resource types and their corresponding scheduling paths. According to matrix O_{bxh} which describes the demand relationships between maintenance modes and maintenance resource types, necessary maintenance resource types for the first maintenance mode can be confirmed. These resources types include the first, the second, the fifth and the eighth. Therefore, the first code, the second code, the fifth code, and the eighth code in [1, 3, 8, 8, 1, 6, 7, 1, 8, 6] are valid codes. For these four types of necessary maintenance resources, their scheduling paths correspond to the first path, the third path, the first path, and the first path, respectively. From these feasible maintenance plans of the Pareto front, enterprises can identify the most appropriate one based on their latest preferences. Carbon tax and carbon credits can be an important decision basis. In this case, chromosome [5, 1, 1, 3, 8, 8, 1, 6, 7, 1, 8, 6] is chosen as the initial predictive maintenance plan. The expected resource scheduling time is 3.5 according to Table 2. Compared to only optimizing the resource allocation scheme in literature [50] and only

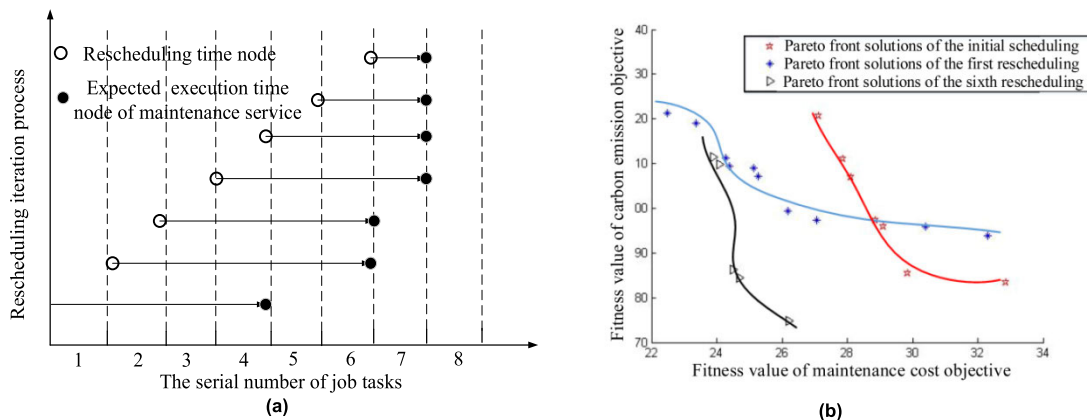


FIGURE 9. Data-driven dynamic maintenance decision process. (a) Rescheduling iteration process. (b) Change of the Pareto front.

optimizing the maintenance time in literature [18], the proposed integrated optimization method can obtain a more feasible maintenance plan.

In response to uncertainties and dynamic characteristics of the maintenance service environment, dynamic adjustment of the unexecuted predictive maintenance plan is implemented. Completion of each job task is chosen as the trigger condition of rescheduling adjustment in this case. It generates a new maintenance plan based on the latest data to replace the original plan. This iteration process is stopped when the time difference between decision time node and corresponding expected execution time node is less than the demand time for resource scheduling. As shown in Fig. 9(a), rescheduling iteration process is terminated after the sixth adjustment. The corresponding Pareto front solutions which are calculated based on the latest forecast data is listed in Table 4. They show that the relatively optimal maintenance time node is before the eighth job task.

TABLE 4. Typical optimal maintenance plans of the pareto front solution set.

Maintenance plan chromosome	Maintenance cost fitness value	Carbon emission fitness value
[8, 1, 4, 1, 5, 5, 2, 3, 5, 4, 7, 5]	26.21	74.83
[8, 1, 3, 1, 5, 5, 2, 3, 5, 4, 7, 5]	24.70	84.51
[8, 1, 6, 1, 5, 5, 2, 3, 5, 4, 7, 5]	24.50	86.28
[9, 1, 3, 3, 5, 5, 2, 3, 5, 4, 7, 5]	24.10	109.74
[9, 1, 6, 3, 5, 5, 2, 3, 5, 4, 7, 5]	23.89	111.52

Analyzing the dynamic rescheduling process, it is found that the execution time node of the maintenance service and the resource configuration scheme are optimized and updated according to the latest dynamic data. The maintenance cost fitness and carbon emission fitness fluctuate constantly even though with the same fault level and maintenance mode. It is because of the dynamic change of the maintenance resource state. Besides, the bearing of grinding roll is expensive and the loss of unit downtime is relatively large for the large vertical mill. Hence, it is more inclined to implement low-complexity maintenance in early fault levels. Fig. 9(b) shows

the change of Pareto front for different rescheduling time nodes. With the dynamic adjustment strategy, the opportunity of obtaining predictive maintenance plans with lower maintenance costs and carbon emissions can be improved, and the adaptability of the maintenance plan is guaranteed as well.

V. CONCLUSION

Scientific and efficient complex equipment maintenance security can not only improve the equipment production efficiency but also play a key role in the path towards green manufacturing. Predictive maintenance further expands this potential. However, prediction accuracy and adaptability of maintenance plans limit the implementation of predictive maintenance. Meanwhile, researchers pay less attention to the environmental impact of the maintenance scheduling process. To address this problem, this paper focuses on the precise decision of predictive maintenance under a ubiquitous create maintenance scheduling environment. A structural framework of information sharing and service network for predictive maintenance scheduling of complex equipment is introduced to achieve real-time perception of equipment objects and maintenance service resource objects. This framework supports the interactive sharing of data across organizational boundaries and expands the schedulable range of distributed maintenance service resources. Carbon emission can also be monitored and controlled based on scheduling process awareness. Then, a mathematical problem model of predictive maintenance decision is established. Carbon emission is introduced as one of the objectives. Through the improved NSGA-II algorithm, a Pareto front solution set corresponding to different preferences is provided to user enterprises. The maintenance time node, the maintenance mode, and the configuration scheme of required maintenance service resources are all integrated into this optimization problem. Considering uncertainties of the maintenance service environment, a data-driven dynamic predictive maintenance decision strategy is applied. Finally, a case study is provided to validate the proposed dynamic predictive maintenance decision method. The proposed integrated intelligent

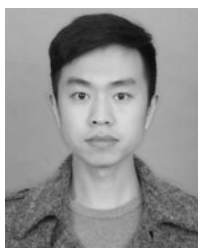
green scheduling optimization method can improve the reliability of a predictive maintenance plan and mining the green performance potential of maintenance scheduling process.

In the next phase of our study, some constraints and assumptions of the mathematical model will be improved to adapt to the actual manufacturing environment. More sources of carbon emissions, and other pollutant emissions during the whole maintenance service process will be considered. Green predictive maintenance with high precision is an important research direction. The research in this paper and future work will provide feasible technical supports in this filed.

REFERENCES

- [1] K. Gupta, R. F. Laubscher, J. P. Davim, and N. K. Jain, "Recent developments in sustainable manufacturing of gears: A review," *J. Cleaner Prod.*, vol. 112, no. 4, pp. 3320–3330, Jan. 2016.
- [2] A. Moldavska and T. Welo, "The concept of sustainable manufacturing and its definitions: A content-analysis based literature review," *J. Cleaner Prod.*, vol. 166, pp. 744–755, Nov. 2017.
- [3] G. Tian, H. Zhang, Y. Feng, D. Wang, Y. Peng, and H. Jia, "Green decoration materials selection under interior environment characteristics: A grey-correlation based hybrid MCDM method," *Renew. Sustain. Energy Rev.*, vol. 81, no. 1, pp. 682–692, Jan. 2018.
- [4] Y. Feng, Z. Hong, Z. Li, H. Zheng, and J. Tan, "Integrated intelligent green scheduling of sustainable flexible workshop with edge computing considering uncertain machine state," *J. Cleaner Prod.*, vol. 246, Feb. 2020, Art. no. 119070, doi: [10.1016/j.jclepro.2019.119070](https://doi.org/10.1016/j.jclepro.2019.119070).
- [5] H. Rødseth and P. Schjøberg, "Data-driven predictive maintenance for green manufacturing," in *Proc. 6th Int. Workshop Adv. Manuf. Autom. (IWAMA)*, Nov. 2016, pp. 36–41.
- [6] M. Behzad, H. Kim, M. Behzad, and H. A. Behambari, "Improving sustainability performance of heating facilities in a central boiler room by condition-based maintenance," *J. Cleaner Prod.*, vol. 206, pp. 713–723, Jan. 2019.
- [7] C. Garrido-Hidalgo, D. Hortelano, L. Roda-Sanchez, T. Olivares, M. C. Ruiz, and V. Lopez, "IoT heterogeneous mesh network deployment for Human-in-the-Loop challenges towards a social and sustainable industry 4.0," *IEEE Access*, vol. 6, pp. 28417–28437, 2018.
- [8] D. Goyal and B. S. Pabla, "Condition based maintenance of machine tools—A review," *J. Manuf. Sci. Technol.*, vol. 10, pp. 24–35, Aug. 2015.
- [9] R. Geng, X. Wang, N. Ye, and J. Liu, "A fault prediction algorithm based on rough sets and back propagation neural network for vehicular networks," *IEEE Access*, vol. 6, pp. 74984–74992, 2018.
- [10] G. Wu, J. Tong, L. Zhang, Y. Zhao, and Z. Duan, "Framework for fault diagnosis with multisource sensor nodes in nuclear power plants based on a Bayesian network," *Ann. Nucl. Energy*, vol. 122, pp. 297–308, Dec. 2018.
- [11] Y. Wu, G. S. Hong, and W. S. Wong, "Prognosis of the probability of failure in tool condition monitoring application—A time series based approach," *Int. J. Adv. Manuf. Technol.*, vol. 76, nos. 1–4, pp. 513–521, Sep. 2014.
- [12] W. Liao, Y. Wang, and E. Pan, "Single-machine-based predictive maintenance model considering intelligent machinery prognostics," *Int. J. Adv. Manuf. Technol.*, vol. 63, nos. 1–4, pp. 51–63, Jan. 2012.
- [13] X. Li and X. Yao, "Multiscale statistical process monitoring in machining," *IEEE Trans. Ind. Electron.*, vol. 52, no. 3, pp. 924–927, Jun. 2005.
- [14] J. Ni, C. Zhang, and S. X. Yang, "An adaptive approach based on KPCA and SVM for real-time fault diagnosis of HVCBs," *IEEE Trans. Power Del.*, vol. 26, no. 3, pp. 1960–1971, Jul. 2011.
- [15] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review," *Mech. Syst. Signal Process.*, vol. 108, pp. 33–47, Aug. 2018.
- [16] B. K. Lad and M. S. Kulkarni, "Optimal maintenance schedule decisions for machine tools considering the user's cost structure," *Int. J. Prod. Res.*, vol. 50, no. 20, pp. 5859–5871, Oct. 2012.
- [17] Q. Liu, M. Dong, F. F. Chen, W. Lv, and C. Ye, "Single-machine-based joint optimization of predictive maintenance planning and production scheduling," *Robot. Comput.-Integr. Manuf.*, vol. 55, pp. 173–182, Feb. 2019.
- [18] W. J. C. Verhagen and L. W. M. De Boer, "Predictive maintenance for aircraft components using proportional hazard models," *J. Ind. Inf. Integr.*, vol. 12, pp. 23–30, Dec. 2018.
- [19] M. De Benedetti, F. Leonardi, F. Messina, C. Santoro, and A. Vasilakos, "Anomaly detection and predictive maintenance for photovoltaic systems," *Neurocomputing*, vol. 310, pp. 59–68, Oct. 2018.
- [20] B. Schmidt and L. Wang, "Cloud-enhanced predictive maintenance," *Int. J. Adv. Manuf. Technol.*, vol. 99, nos. 1–4, pp. 5–13, Jun. 2016.
- [21] H. Rødseth, T. Skarlo, and P. Schjøberg, "Profit loss indicator: A novel maintenance indicator applied for integrated planning," *Adv. Manuf.*, vol. 3, no. 2, pp. 139–150, Jun. 2015.
- [22] X. F. Yao, Z. Y. Sun, L. Li, and H. Shao, "Joint maintenance and energy management of sustainable manufacturing systems," in *Proc. ASME Int. Manuf. Sci. Eng. Conf.*, Jun. 2015, pp. 1–6.
- [23] ICB. (2016). *Green Monitor-Online Maintenance and Manufacturing Support*. Accessed: Feb. 4, 2016. [Online]. Available: <http://greenmonitor.icb.bg/>
- [24] J. Wan, S. McLoone, P. English, P. O'Hara, and A. Johnston, "Predictive maintenance for improved sustainability—An ion beam etch endpoint detection system use case," *Commun. Comput. Inf. Sci.*, vol. 463, no. 1, pp. 147–156, 2016.
- [25] R. B. M. Consulting, "Predictive maintenance: Potential burst point in industrial digitalization," *China Ind. Inform. Technol.*, vol. 11, pp. 72–78, Mar. 2017, doi: [10.19609/j.cnki.cn10-1299/f.2017.11.010](https://doi.org/10.19609/j.cnki.cn10-1299/f.2017.11.010).
- [26] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mech. Syst. Signal Process.*, vol. 20, no. 7, pp. 1483–1510, Oct. 2006.
- [27] K. Wang, H. Li, Y. Feng, and G. Tian, "Big data analytics for system stability evaluation strategy in the energy Internet," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 1969–1978, Aug. 2017.
- [28] X. Y. Yang and F. Y. Hu, "Research on the modeling and uncertainty analysis of collaborative MRO service chain of complex product," *Comput. Integ. Manuf. Syst.*, vol. 25, pp. 326–339, Feb. 2019, doi: [10.13196/j.cims.2019.02.006](https://doi.org/10.13196/j.cims.2019.02.006).
- [29] H. D. Ardakani and J. Lee, "A minimal-sensing framework for monitoring multistage manufacturing processes using product quality measurements," *Machines*, vol. 6, no. 1, p. 1, Jan. 2018, doi: [10.3390/machines6010001](https://doi.org/10.3390/machines6010001).
- [30] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manuf. Lett.*, vol. 3, pp. 18–23, Jan. 2015.
- [31] J. Lee, H. D. Ardakani, S. H. Yang, and B. Bagheri, "Industrial big data analytics and cyber-physical systems for future maintenance & service innovation," in *Proc. 4th Int. Conf. Trans.-Life Eng. Serv. (TESConf)*, vol. 3, pp. 3–7, Jan. 2015.
- [32] Y. Gao, Y. Feng, Z. Zhang, and J. Tan, "An optimal dynamic interval preventive maintenance scheduling for series systems," *Rel. Eng. Syst. Saf.*, vol. 142, pp. 19–30, Oct. 2015.
- [33] N. Gebraeel, "Sensory-updated residual life distributions for components with exponential degradation patterns," *IEEE Trans. Autom. Sci. Eng.*, vol. 3, no. 4, pp. 382–393, Oct. 2006.
- [34] R. Arno, N. Dowling, and R. J. Schuerger, "Equipment failure characteristics and RCM for optimizing maintenance cost," *IEEE Trans. Ind. Appl.*, vol. 52, no. 2, pp. 1257–1264, May 2016.
- [35] Y. Feng, Z. Hong, G. Tian, Z. Li, J. Tan, and H. Hu, "Environmentally friendly MCDM of reliability-based product optimisation combining DEMATEL-based ANP, interval uncertainty and vlse kriterijumska optimizacija kompromisno resenje (VIKOR)," *Inf. Sci.*, vols. 442–443, pp. 128–144, May 2018.
- [36] S. Zhu, Z. Jiang, H. Zhang, G. Tian, and Y. Wang, "A carbon efficiency evaluation method for manufacturing process chain decision-making," *J. Cleaner Prod.*, vol. 148, pp. 665–680, Apr. 2017.
- [37] S. Yu, Y.-M. Wei, H. Guo, and L. Ding, "Carbon emission coefficient measurement of the coal-to-power energy chain in China," *Appl. Energy*, vol. 114, pp. 290–300, Feb. 2014.
- [38] C. Liu, J. Yang, J. Lian, W. Li, S. Evans, and Y. Yin, "Sustainable performance oriented operational decision-making of single machine systems with deterministic product arrival time," *J. Cleaner Prod.*, vol. 85, pp. 318–330, Dec. 2014.
- [39] J. Wang, S. Yao, J. Sheng, and H. Yang, "Minimizing total carbon emissions in an integrated machine scheduling and vehicle routing problem," *J. Cleaner Prod.*, vol. 229, pp. 1004–1017, Aug. 2019.
- [40] T. Bektaş and G. Laporte, "The pollution-routing problem," *Transp. Res. B, Methodol.*, vol. 45, no. 8, pp. 1232–1250, Sep. 2011.

- [41] J. Zhao, S. Liu, M. Zhou, X. Guo, and L. Qi, "Modified cuckoo search algorithm to solve economic power dispatch optimization problems," *IEEE/CAA J. Automatica Sinica*, vol. 5, no. 4, pp. 794–806, Jul. 2018.
- [42] H. Zhu, G. Liu, M. Zhou, Y. Xie, and Q. Kang, "Dandelion algorithm with probability-based mutation," *IEEE Access*, vol. 7, pp. 97974–97985, 2019.
- [43] J. Li, G. Liu, C. Yan, and C. Jiang, "Robust learning to rank based on portfolio theory and AMOSA algorithm," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 6, pp. 1007–1018, Jun. 2017.
- [44] S. Wang, G. Liu, and S. Gao, "A hybrid discrete imperialist competition algorithm for fuzzy job-shop scheduling problems," *IEEE Access*, vol. 4, pp. 9320–9331, 2016.
- [45] K. Gao, Z. Cao, L. Zhang, Z. Chen, Y. Han, and Q. Pan, "A review on swarm intelligence and evolutionary algorithms for solving flexible job shop scheduling problems," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 4, pp. 904–916, Jul. 2019.
- [46] H. Li, S. H. Mi, Q. F. Li, X. Y. Wen, D. P. Qiao, and G. F. Luo, "A scheduling optimization method for maintenance, repair and operations service resources of complex products," *J. Intell. Manuf.*, vol. 27, no. 2, pp. 1–19, Mar. 2018.
- [47] X. Guo, S. Liu, M. Zhou, and G. Tian, "Dual-objective program and scatter search for the optimization of disassembly sequences subject to multiresource constraints," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 3, pp. 1091–1103, Jul. 2018.
- [48] X. Guo, M. Zhou, S. Liu, and L. Qi, "Lexicographic multiobjective scatter search for the optimization of sequence-dependent selective disassembly subject to multiresource constraints," *IEEE Trans. Cybern.*, to be published, doi: [10.1109/TCYB.2019.2901834](https://doi.org/10.1109/TCYB.2019.2901834).
- [49] D. W. Corne, J. D. Knowles, and M. J. Oates, "The Pareto envelope-based selection algorithm for multiobjective optimization," in *Proc. Int. Conf. Parallel Probl. Solving Nat. (PPSN)*, vol. 1917, 2000, pp. 839–848.
- [50] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multi-objective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
- [51] Y. Feng, Y. Gao, G. Tian, Z. Li, H. Hu, and H. Zheng, "Flexible process planning and end-of-life decision-making for product recovery optimization based on hybrid disassembly," *IEEE Trans. Autom. Sci. Eng.*, vol. 16, no. 1, pp. 311–326, Jan. 2019.
- [52] Y. Feng, M. Zhou, G. Tian, Z. Li, Z. Zhang, Q. Zhang, and J. Tan, "Target disassembly sequencing and scheme evaluation for CNC machine tools using improved multiobjective ant colony algorithm and fuzzy integral," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 12, pp. 2438–2451, Dec. 2019.
- [53] G. Tian, Y. Ren, Y. Feng, M. Zhou, H. Zhang, and J. Tan, "Modeling and planning for dual-objective selective disassembly using and or graph and discrete artificial bee colony," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2456–2468, Apr. 2019.
- [54] X. Zan, Z. Wu, C. Guo, and Z. Yu, "A Pareto-based genetic algorithm for multiobjective scheduling of automated manufacturing systems," *Adv. Mech. Eng.*, vol. 12, no. 1, Jan. 2020, Art. no. 168781401988529, doi: [10.1177/1687814019885294](https://doi.org/10.1177/1687814019885294).
- [55] L. Li, F. Basile, and Z. Li, "An approach to improve permissiveness of supervisors for GMECs in time Petri net systems," *IEEE Trans. Autom. Control*, vol. 65, no. 1, pp. 237–251, Jan. 2020.
- [56] Y. Liu, K. Cai, and Z. Li, "On scalable supervisory control of multiagent discrete-event systems," *Automatica*, vol. 108, Oct. 2019, Art. no. 108460, doi: [10.1016/j.automatica.2019.06.012](https://doi.org/10.1016/j.automatica.2019.06.012).



SHANGHUA MI received the B.S. and M.S. degrees in mechanical engineering from the Zhengzhou University of Light Industry, Zhengzhou, China, in 2013 and 2016, respectively. He is currently pursuing the Ph.D. degree with the State Key Laboratory of CAD&CG, School of Mechanical Engineering, Zhejiang University. He is currently with the State Key Laboratory of CAD&CG and State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University. His recent research interests include manufacturing services, multiobjective evolutionary algorithms, and intelligent scheduling and optimization.



YIXIONG FENG received the B.S. and M.S. degrees in mechanical engineering from Yanshan University, Qinhuangdao, China, in 1997 and 2000, respectively, and the Ph.D. degree in mechanical engineering from Zhejiang University, Hangzhou, China, in 2004.

He is currently a Professor with the Department of Mechanical Engineering, Zhejiang University, China, and also the member of the State Key Laboratory of Fluid Power and Mechatronic Systems, China. He has published more than 100 journals and conference proceedings papers in the above research areas. He has been the Principal Investigator of four projects supported by the National Natural Science Foundation of China and one project supported by the National High-Tech Research and Development Program of China (863 Program). His research focuses on mechanical product design theory, intelligent automation, and advance manufacture technology. He is the winner of Zhejiang Province Outstanding Youth Fund and the winner of National Outstanding Youth Fund.



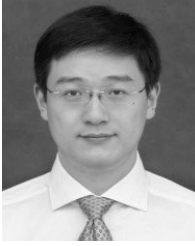
HAO ZHENG received the B.S. degree in mechanical engineering from Southwest Jiaotong University, Chengdu, China, in 2010, and the Ph.D. degree in mechanical engineering from Zhejiang University, Hangzhou, China, in 2017. He was with the State Key Laboratory of CAD&CG and State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University. He is currently a Research Assistant with the Hangzhou Innovation Institute, Beihang University. His

recent research interests include data-driven design, decision-making and optimization, multiobjective evolutionary algorithms, and machine learning.



ZHIWU LI (Fellow, IEEE) received the B.S. degree in mechanical engineering, the M.S. degree in automatic control, and the Ph.D. degree in manufacturing engineering from Xidian University, Xi'an, China, in 1989, 1992, and 1995, respectively. In 1992, he joined Xidian University. Over the past decade, he was a Visiting Professor with the University of Toronto, Technion—Israel Institute of Technology, Martin-Luther University, the Conservatoire National des Arts et Metiers,

Meliksah Universitesi, King Saud University, and the University of Cagliari. He is currently with the Institute of Systems Engineering, Macau University of Science and Technology, Taipa, Macau. His current research interests include Petri net theory and application, the supervisory control of discrete event systems, work flow modeling and analysis, system reconfiguration, game theory, and data and process mining. He is a member of the Discrete Event Systems Technical Committee of the IEEE Systems, Man, and Cybernetics Society, and a member of IFAC Technical Committee on Discrete Event and Hybrid Systems, from 2011 to 2014. He was a recipient of an Alexander von Humboldt Research Grant, an Alexander von Humboldt Foundation, Germany, and Research in Paris, France. He is the Founding Chair of the Xi'an Chapter of the IEEE Systems, Man, and Cybernetics Society.



YICONG GAO received the B.S. degree in mechanical engineering from the East China University of Science and Technology, Shanghai, China, in 2005, and the Ph.D. degree in mechanical engineering from Zhejiang University, Hangzhou, China, in 2011.

He is currently a Research Assistant with the Department of Mechanical Engineering, Zhejiang University, and also the member of the State Key Laboratory of Fluid Power Transmission and Control, Zhejiang University, China. His research focuses on mechanical product design theory, intelligent automation, and advance manufacture technology. He has been the Principal Investigator of two projects supported by the National Natural Science Foundation of China.



JIANRONG TAN received the B.S. and M.S. degrees in mechanical engineering and electronic engineering from The Open University of China, Beijing, China, in 1982, the M.S. degree in engineering from the Huazhong University of Science and Technology, Wuhan, China, in 1985, and the Ph.D. degree in mathematics from Zhejiang University, Hangzhou, China, in 1987.

He is currently a specially appointed Professor in Zhejiang University, a Doctorial Supervisor, and an Academician of the Chinese Academy of Sciences, the Dean of mechanical engineering, the Associate Supervisor of the CAD&CG State Key Laboratory, the Head of the Institute of Engineering and Computer Graphics, Zhejiang University, and the Chief Supervisor of engineering graphics state fundamental courses. His research focuses on mechanical designing and theory, digitalized designing, and manufactory. He has published eight pieces of monograph or compile, 142 pieces of articles indexed by SCI/EI, with more than 1600 times. He gathered his 15 years of working experience in manufactory and his theory in science, and proposed the technique in combination of batch and customization which is used for multitudinous customization, the status in engineering transition, the fuzzy status, the technology simulation of random status modeling and digitalized prototype integration, the combination of figures and geometry in multicomponent correlation in intricate equipment, and the analysis of multilevel disposing and multiparameter matching. He received the National Prize for four times, which includes the second prize in National Technology Progress twice and the first prize in National Excellent Education Achievement. He has also received the first prize in Provincial Level Technology Progress for six times. He transforms his technology into the software and got 12 copyrights of computer software, which achieved a lot in manufacturing enterprises.

• • •