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Perception Data-Driven Optimization of Manufacturing Equipment Service Scheduling in Sustainable Manufacturing

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Abstract: Both sustainable manufacturing and manufacturing service are the trends in industry because they are regarded as ways to reduce the resource cost and energy consumption in manufacturing process, to improve the flexibility and responding speed to customers' demand, and to improve the production efficiency. In order to improve the sustainability of manufacturing equipment services in job shop, this paper presents a multi-objective joint model of energy consumption and production efficiency. The model is related to multi-conditions of manufacturing equipment services. The conditions are monitored in real-time to drive a multi-objective dynamic optimized scheduling of manufacturing services. In order to solve the multi-objective problem, an enhanced Pareto-based bees algorithm (EPBA) is proposed. In order to ensure the variety of population, to prevent the premature convergence, and to improve the searching speed, several key technologies are utilized such as variable neighborhood searching, mutation and crossover operation, fast non-dominated ranking, critical path local search, archive Pareto set, critical path taboo set, etc. Finally, the proposed method is evaluated and it shows better performance in static and dynamic scenarios compared with the existing optimization algorithms.
Keywords: Sustainable manufacturing, manufacturing equipment service, perception data-driven, bees algorithm, optimized scheduling

1. Introduction

Sustainable development has been put forward since 1987 by the United Nations [1]. It is regarded as a way to achieve the balance of social, environment, and economy. According to statistics, the manufacturing sector consumes 90% of the total energy consumption of industry [2]. As the resources and energy in the earth are limited and getting fewer and fewer, sustainable manufacturing is gaining more and more attention. Energy efficient manufacturing is an important part of sustainable manufacturing. It aims to produce the same product with less energy consumption. For manufacturing enterprises, they should struggle with the increasing resource and energy prices to produce competing products with less resource and energy consumption. Moreover, manufacturing enterprises should take the responsibility of saving energy and reducing the carbon emission. Therefore, it is important for them to produce products in a sustainable way.

In the present world, the products are always completed by many participants. They need to collaborate with each other in the manufacturing process. Therefore, a manufacturing model which facilitates the collaboration of participants in manufacturing is very important. Cloud manufacturing [3-7] adopts a service-oriented manufacturing model and has been widely recognized as a novel business model to support the operations of future factories. In cloud manufacturing, all the manufacturing resources and capabilities are encapsulated into services and can be traded via internet. Enterprises can buy and use services they need. In such a way, enterprises can collaborate with each other conveniently. Xu et al. proposed the framework and methodologies of a service-oriented sustainable manufacturing [8]. Service-oriented manufacturing model is used to improve the efficiency of production and reduce the cost. By using this model, the optimized production processes and highly efficient utilization of different types of resources can effectively contribute to sustainable manufacturing such as reduction and recycling of raw material, reduction of energy conservation, waste, pollution, etc. Consequently, integrating service-oriented manufacturing with sustainable manufacturing will bring about a promising future.

Manufacturing equipments refer to physical devices in manufacturing systems, such as CNC machines, sensors, etc. They are the foundations of manufacturing. The scheduling of manufacturing equipments has a great influence on the energy consumption, time consumption, and cost of production. Due to the heterogeneous nature and diversity of manufacturing equipments, the long production cycle, the various production processes, and the vulnerability to uncertain factors such as equipment faults and task changing, traditional manual scheduling of manufacturing process cannot cope with them. The aforementioned service-oriented manufacturing model can be used to the schedule manufacturing equipments effectively. In this model, manufacturing equipments are encapsulated as services. Manufacturing equipment service is the logical entity of manufacturing cell and it can be consisted of a number of functions of the manufacturing equipment, a group of machining unit or an assembly line, etc. The combination of services can adapt to dynamic production environment and provide flexibility and efficiency of the production. The way of applying manufacturing equipment services is that they can be matched to specific manufacturing task of the business layer through modeling and description of manufacturing equipment services. The scheduling of manufacturing equipments is then realized by service scheduling. Considering that the manufacturing equipment plays an important role in manufacturing, the paper focuses on the management of manufacturing equipment services to improve the sustainability of manufacturing, especially the energy-efficiency of manufacturing.

2. State of The Art

In the area of sustainability-oriented shop scheduling, He et al. studied task-oriented flexible job-shop scheduling problem, in order to reduce the energy consumption of manufacturing system [9]. Fang et al. considered peak power load and energy consumption in addition to cycle time in shop scheduling and enhanced the of sustainability of manufacturing in the shop [10]. Bruzzone et al. established a energy-aware model of the flexible flow shop and proposed a scheduling algorithm based on mixed integer programming [11]. Although their studies aimed to reduce energy consumption of the shop under certain conditions, more complex multi-objective problems were not studied. Dai et al. proposed an improved genetic-simulated annealing algorithm to make a trade-off between the make-span and the total energy consumption of the flow shop [12]. Other factors such as resource consumption were not considered. Du et al. considered make-span and energy consumption as well and developed a Preference Vector Ant Colony System to search for a set of Pareto-optimal solutions using meta-heuristics [13]. The algorithm showed better performance than some well known genetic algorithms. Wang et al. considered manufacturing systems with multiple machines and buffers and integrated electricity consumption into system modeling [14, 15]. Solution of joint production and energy scheduling problem was discussed. Energy consumption is a very important issue that should be considered in the manufacturing service and resource selection and scheduling, and it has attracted the attention from many researchers. For example, in order to realize the energy efficient manufacturing service selection and scheduling, an Internet of thing (IoT) and cloud computing based energy consumption data collection method was designed by Tao et al [16], and a device for collecting energy consumption data was designed and developed by Tao et al [17]. The above method and device proposed by Tao et al. [16, 17] can be used to effective collect energy consumption data in a real time and dynamical way, which is widely referenced by the researchers in related fields, and has been widely used by practitioner in industry both in China and Europe. These studies focus on the energy consumption issue of manufacturing. However, to increase the sustainability of manufacturing, more factors should be considered.

There are some studies which consider the disturbance in manufacturing and propose dynamic scheduling of manufacturing. Zhang et al. considered the energy consumption and the unexpected events occurring in flexible manufacturing system and used the genetic algorithm with elite strategy to optimize the energy consumption and scheduling efficiency simultaneously [18]. Gholami et al. considered dynamic events in real-world environments and the unavailability of machines such as unanticipated breakdowns or preventive maintenance, and used genetic algorithm to minimize the expected makespan and mean tardiness [19]. Nguyen et al. developed four multi-objective genetic programming-based hyper-heuristic methods for automatic design of job shop scheduling policies [20]. The proposed methods could be employed in stochastic and dynamic job shops.

On manufacturing services, Xu et al. proposed a service oriented sustainable manufacturing framework which consisted of perception layer, data layer, service layer and application layer [8]. Wang et al. proposed a new adaptive process planning method, Function Blocks were introduced to the monitoring of job shop and the control of manufacturing equipment [21, 22]. The Functions were data and event driven. Scheduling algorithms were encapsulated in Function Blocks. Tao et al. firstly investigated the relation of cloud computing, internet of things, and cloud manufacturing, and proposed a Cloud Computing and Internet of Things based Cloud Manufacturing Service System [23], and then Tao et al. [24] proposed a parallel method for service composition optimal-selection in cloud manufacturing system, and a new method or dynamic migration of virtual machines in cloud computing [25]. Tao et al. also studied the key issues on manufacturing service and established QoS based model for optimization of manufacturing services [26]. Xia et al. developed an improved ant colony algorithm to realize dynamic combination of optimization services [27]. Xiang et al. considered the importance of energy consumption in cloud manufacturing services and proposed a framework for energy consumption evaluation of cloud manufacturing service [28]. Tao et al. [7] studied the intelligent management of manufacturing service from a lifecycle perspective, and first proposed the concept of manufacturing service network [29] and its scale-free characteristics [30], which developed a new research field both in the field of manufacturing and service computing. It can be concluded that sustainable manufacturing has not been adopted widely in manufacturing services and this should be studied future to improve the sustainability of manufacturing.

Besides the above studies on energy efficient manufacturing mostly in an operational research view, there are many studies on engineering driven approaches. Many software packages such as Simu8, 3DCreate, Arena, Automod, Plant Simulation, Witness, ProModel, ExtendSIM, Simio, Flexsim, Anylogic, Enterprise Dynamics, Gold-Sim and ongoing research have been developed or studied to model and simulate energy and environmentally related aspects in manufacturing system [34]. Salonitis et al. summarized the engineering methods to make manufacturing system more energy efficient, such as switching off equipment at end of shift or powering down clean room air handling when not in use at night, and harvesting energy etc. [35].

The use of sensors in sustainable manufacturing is also a hot topic. Behrendt et al. Vijayaraghavan and Dornfeld correlated energy data from process equipment, ancillary equipment, and embedded sensors with the operations being performed in the manufacturing system, in order to reduce the energy consumption of machine tools and improve the environmental performance of manufacturing system [31]. O'Driscoll and O'Donnell provide a review on industrial power and energy metering to enable a sustainable energy future of manufacturing [32]. Duque Ciceri et al. regarded RFID as powerful tools for gathering product lifecycle data and thus enabled a more sustainable development, engineering, manufacturing, use and disposal of products [33].

Although lots of researches have been done in sustainable manufacturing, service–oriented manufacturing, and shop scheduling, the current studies still have shortages as follows:

(1) Currently, lots of achievements have been achieved on manufacturing service description, service quality evaluation, the service optimization, etc., and they show great prospect for manufacturing enterprises. However, how to effectively schedule manufacturing service to save energy consumption and thus improve sustainability is still a problem.

(2) The goal of traditional shop scheduling is mainly to improve the production efficiency and reduce the cost. It does not consider the environmental aspects, especially the energy consumption. A joint model of energy consumption and production efficiency is lack of and the shop scheduling based on this model has not been studied sufficiently. It is imperative to study the service scheduling under joint production capacity and energy consumption constraints.

(3) Existing shop scheduling can hardly deal with various emergencies in production process and this results in a big gap between the real production and expected ones. There is a lack of research on real-time data acquisition and real-time event management in manufacturing. In fact, data-driven scheduling of manufacturing service based on by sensory data will enable dynamic scheduling of manufacturing services and enable agility and practicability of manufacturing services.

This paper sets up multi-objective dynamic scheduling model of shop manufacture equipment services based on sensory data. A multi-objective optimization of joint energy consumption and the production efficiency is realized. This paper is organized as follows: section 3 describes the proposed framework and defines the problem; section 4 puts forward a joint energy consumption and production efficiency model for shop manufacturing equipments; section 5 puts forward multi-objective dynamic scheduling optimization of manufacturing equipment services; section 6 discusses the effectiveness of the scheduling method with examples; finally, the conclusions are gathered in section 7.

3. Framework and Problem Description

3.1 Framework

Scheduling of shop manufacturing equipment services is to generate an appropriate service execution path under certain constraints and to achieve the optimal performance indexes. For sustainable manufacturing, the goal of service scheduling is to reduce the energy and resource consumption of manufacturing, and save costs for enterprises. The general framework of scheduling of manufacturing equipment services under energy consumption and production efficiency constraint is proposed and shown in Fig.1. The service requests are transmitted to the service platform with parameters describing the requests of service demanders. The manufacturing equipments are encapsulated into services with parameters describing their abilities and registered in the service platform. The service requests will be decomposed in the service platform and matched with manufacturing equipment services. The services will then be scheduled and combined to perform manufacturing. Sensors are used to virtualize and servilize manufacturing equipment and to monitor the energy and production efficiency of manufacturing equipment services. As events such as equipment faults always happen, these events will cause the change of energy and production efficiency. If the change of energy and production efficiency of original production plan exceeds a threshold, a rescheduling will be performed and the production plan will be modified.

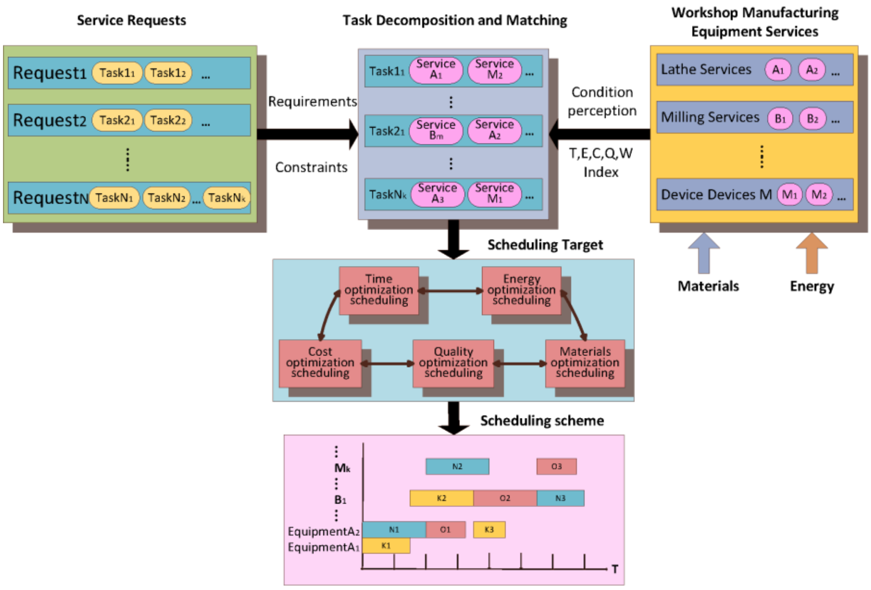

Fig.1 Framework of scheduling of manufacturing equipment services

3.2 Perception method of energy and production condition of manufacturing equipments

The perception of energy and production condition gives information to dynamic manufacturing service scheduling and is realized by various sensors. Conditions which are relative to energy and production efficiency are perceived, including electric energy consumption, material consumption, time consumption, cost consumption, the quality of product, and other conditions related to the machine faults, such as temperature, stress, vibration, etc. The electric energy can be measured by power meters and can be used to evaluate the energy-efficiency of machines. The production related conditions, such as the time consumption, material consumption, can be perceived by the RFID tags attached to products, work-in-process and raw materials. Information of quality and cost of products can also be stored in RFID tags. But they should be perceived by sensors such as surface roughness tester. The energy and production conditions are transferred to a database via internet as shown by Fig.2.

The choosing of sensors is very important. A detailed discussion of power meter can be found in [32]. Generally, high sampling rate is required to monitor the transient events of the current that appear and disappear within a faction of a second. For power monitoring of machines, the specific sampling rate may not need to be very high but should be qualified enough. The power meter should be carefully selected as it is the main price driver of power meter. The sampling rate of RFID read is high but the read rate is affected by many factors. Some methods in [36] can be used to improve the read rate. The cost is also a main issue in the application of RFID tags and RFID readers. Therefore, the benefits of RFID technology should be weighed against its cost before its implementation.

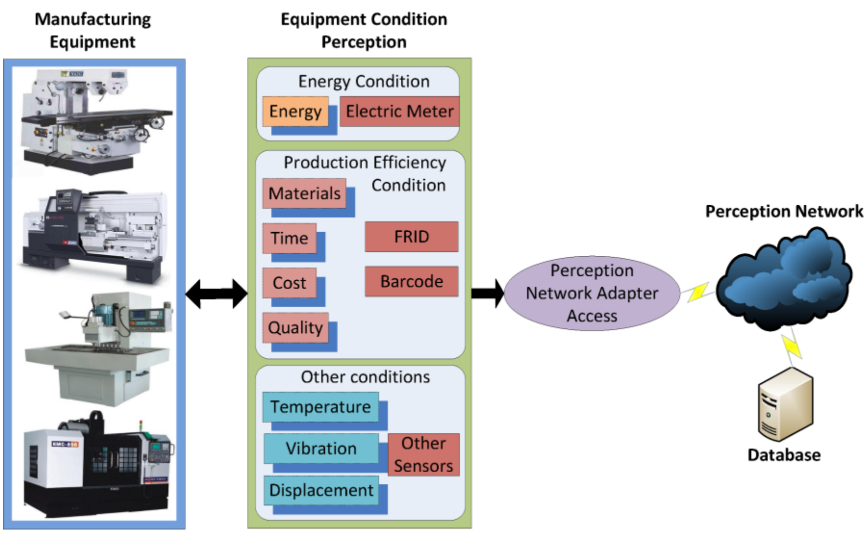

Fig.2 Energy and production condition perception for manufacturing equipments

3.3 Manufacturing equipment servilization

The servilization of manufacturing equipments includes two steps. The first step is equipment vitalization. The manufacturing equipments are virtualized by mapping the perceived information from sensors or information gathered manually to description models of manufacturing equipments, as shown by Fig.3. Some of the information about the equipments, such as the basic information about the manufacturing equipments, is provided by equipment holders. The second step is service servilization. Virtual manufacturing equipments are encapsulated into Web Services which are platform independent, autonomous, and interoperable. Then the services are registered in the manufacturing equipment service platform. Service users can apply and use these services.

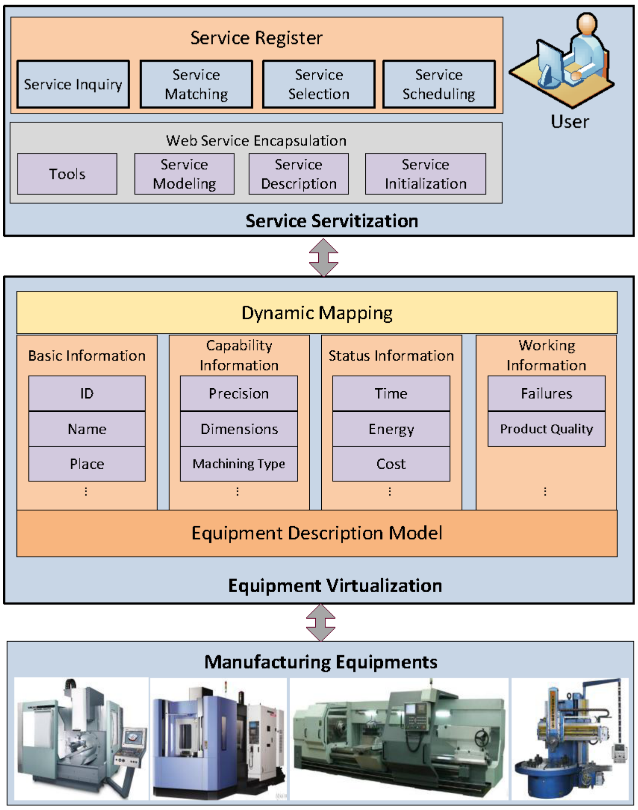

Fig.3 Manufacturing equipment service model

Suppose that there are M manufacturing equipments in the shop and they are encapsulated as M services and registered in the service platform. There are N manufacturing equipment service requests. Every manufacturing equipment service request corresponds to a task $T_i, i \in [1, N]$ and will be decomposed into subtasks $T_i = [t_1, t_2, \cdots, t_k]$. in the manufacturing service platform. There is sequential relationship between the subtasks. The subtasks will then be matched with manufacturing equipment services. For each subtask t_j, the candidate set of manufacturing equipment services are $mt_j = [m_1, m_2, \cdots, m_l], l \in [1, M]$. For each manufacturing equipment service $m_f, f \in [1, M]$, the candidate set of subtasks is $tm_f = [t_{11}, t_{12}, \cdots, t_{ij}], i \in [1, N], j \in [1, k]$. The purpose of scheduling optimization is to select proper manufacturing equipment services to finish the task and achieve the optimal results. Considering that, some disturbances, such as task inserting, task failure or machine faults may occur. The dynamic scheduling of manufacturing equipment services should deal with these situations. In order to simplify the problem, this paper makes the following assumptions:

(1) At the same time, one equipment service only responses to one task of a service request, other tasks need to wait.

(2) At the same time, one task can only be allocated to one equipment service.

(3) Among the subtasks of one service request, each task needs to obey a certain order.

(4) When a disturbance occurs and a new scheduling is needed, unaffected tasks continue until they are completed.

(5) The states of machines (e.g. warming, setting up, working, no-load and waiting, etc.) have strong influences on sustainable scheduling. Warming is needed before the machine is ready to be used. Setting up is a state between warming and working. To reduce the complexity of the scheduling, three states, namely working, no-load and waiting, are considered in this paper. However, other states can be taken into account if necessary.

(6) The total energy consumption of manufacturing equipment for each specific subtask includes the energy consumption of machining and peripheral systems such as coolant system.

The goal of sustainable scheduling of manufacturing equipment services in this paper is the harmony of economy, environment and society. Specifically, the goal is shown in Formula (1). That is to minimize the time consumption T, cost C, material consumption W and the energy consumption E, and maximize the product quality Q. By this way, the production efficiency and energy consumption are expected to be optimized at the same time.

$$F = [f_1, f_2, f_3, f_4, f_5] = [\min T, \min C, \min W, \min E, \max Q] \tag{1}$$

$$f_1(T) = max(T_i) = max(\sum_{j=1}^{n} T_{ijm}) \tag{2}$$

$$f_2(C) = \sum_{i=1}^{N} C_i = \sum_{i=1}^{N}\sum_{j=1}^{n} C_{ijm} \tag{3}$$

$$f_3(W) = \sum_{i=1}^{N} W_i = \sum_{i=1}^{N}\sum_{j=1}^{n} W_{ijm} \tag{4}$$

$$f_4(E) = \sum_{i=1}^{N} E_i = \sum_{i=1}^{N}\sum_{j=1}^{n} E_{ijm} \tag{5}$$

$$f_5(Q) = \sum_{i=1}^{N} Q_i = \sum_{i=1}^{N}\sum_{j=1}^{n} Q_{ijm} \tag{6}$$

4. Joint Energy and Production Modeling of Manufacturing Equipment Services

When manufacturing service application is submitted to the job shop manufacturing service platform, it is decomposed and matched with a set of services depending on the task requirements and equipment service capability. A candidate set of services meet the requirements of service demander will be assigned by the service platform. The candidate service set is $S = \{S_1, S_2, \cdots, S_j\} = \{s_1, s_2, \cdots, s_k, \cdots, s_c\}$, where s_k refers to a unit service, j services are decomposed into c unit service. $R = \{r_1, r_2, \cdots, r_p, \cdots, r_m\}$ refers to m manufacturing sources. $S_p = \{s_k, s_{k+1}, \cdots, s_n\}, S_p \subseteq S$ refers the unit services provided by manufacturing source r_p, every unit service can fulfill a subtask.

Sustainable scheduling of manufacturing equipment service can be described as: according to the decomposed manufacturing tasks, the candidate manufacturing equipment services are selected to form the candidate service set under constraints;

manufacturing tasks are allocated to manufacturing equipment services to achieve optimal objectives. This paper considers the total time *T*, the total energy consumption *E*, the product quality *Q*, the total cost *C*, and the total material consumption *W* as objectives.

The three different states for manufacturing equipments, namely working, no-load and waiting, is (M_1, M_2, M_3). The time consumption *T*, energy consumption *E*, quality *Q*, cost *C*, and material *W* for each state are calculated by formula (7)-(12) respectively, (p_1, p_2, p_3) indicates the power of manufacturing equipment in the states of working, no-load and waiting.

$$(M_1, M_2, M_3)$$

$$T \quad t_1 \quad t_2 \quad t_3 \quad t = \sum_{i=1}^{3} t_i \tag{7}$$

$$E \quad e_1 \quad e_2 \quad e_3 \quad e = \sum_{i=1}^{3} e_i \tag{8}$$

$$Q \quad q_1 \quad q_2 \quad q_3 \quad q = \sum_{i=1}^{3} q_i \tag{9}$$

$$C \quad c_1 \quad c_2 \quad c_3 \quad c = \sum_{i=1}^{3} c_i \tag{10}$$

$$W \quad w_1 \quad w_2 \quad w_3 \quad w = \sum_{i=1}^{3} w_i \tag{11}$$

$$\mathrm{e} = e_1 + e_2 + e_3 = \int_0^{t_1} p_1 dt + \int_0^{t_2} p_2 dt + \int_0^{t_3} p_3 dt \tag{12}$$

4.1 Objective function

Total time: Supposing that the time for completing a subtask p by equipment *m* is t_{mp}, and the time for completing a subtask $p-1$ is $t_{m(p\text{-}1)}$. t_p is the processing time of subtask p, then $t_{mp} = t_{m(p\text{-}1)} + t_p$. The total time to complete a task by equipment *m* is $T = \sum_{p=1}^{n} t_{mp}$. The objective is to minimize the maximum total time consumption T of for all equipments.

$$min(T) = min\left(\underset{m}{max}\left(\sum_{p=1}^{n} t_{mp} \right) \right) \tag{13}$$

Total energy consumption: The manufacturing process consumes electricity, compressed air, diesel oil and other energy sources. After completing n tasks with k kinds of energy resources, the energy consumption of manufacturing equipment m is $e_m = \sum_{i=1}^{k} e_i \lambda_i$, where λ_i is the conversion coefficient for the i-th kind of energy consumption. After completing the whole manufacturing process the comprehensive energy consumption is $E=\sum_{j=1}^{n}e_m=\sum_{j=1}^{n}\sum_{i=1}^{k}e_i\lambda_i$. The objective function of total energy consumption is

$$min(E)=min\left(\sum_{j=1}^{n}e_m\right)=min\left(\sum_{j=1}^{n}\sum_{i=1}^{k}e_i\lambda_i\right) \tag{14}$$

Machining quality. Quality includes dimensional accuracy, etc. The objective function quality is shown by formula (15), where q_i is the i-th evaluation index, δ_i is the weight of i-th evaluation index.

$$max(Q)=max\left(\sum_{i=1}^{n}\delta_i q_i\right) \tag{15}$$

Total cost: The use of any manufacturing equipment will inevitably bring costs, including the equipment cost, logistic cost, manpower cost. The objective function of total cost is shown by formula (16), where c_i is the i-th cost, η_i is the weight for the i-th cost.

$$min(C)=min\left(\sum_{i=1}^{n}\eta_i c_i\right) \tag{16}$$

Total material consumption: The manufacturing process consumes materials, such as lubricating oil, cooling water, raw materials. Its objective function is shown by formula (17), where m_i is the evaluation index of material i, β_i is the weight of the i-th material evaluation index.

$$min(W)=min\left(\sum_{i=1}^{n}\beta_i m_i\right) \tag{17}$$

Based on five above objectives, the multi-objective optimization problem can be described as formula (18).

$$F=(f_T,f_E,f_Q,f_C,f_W,)=min(T,E,C,W)\ and\ max(Q)=min\left(T,E,{}^{1}\!/_{Q},C,W\right) \tag{18}$$

4.2 Constraints

Manufacturing equipment resource constraint: The set of services which can be completed by a manufacturing equipment resource is $S=\{S_1,S_2,\ldots S_l\ldots S_m\}$. Each service is independent.

Delivery time constraint: The completion time T cannot be later than the delivery time T_c.

$$T_c\geq T=\max_m\left(\sum_{p=1}^{n}t_{mp}\right) \tag{19}$$

The manufacture process constraint: The subtasks of the same service application obey process constraints. Assuming that the subtasks $p-1$ and p were to be completed on the equipment r_n and r_m respectively, they should follow formula (20).

$$t_{n(p-1)}\leq t_{mp}-t_p \tag{20}$$

Energy consumption constraint: The total energy consumption E cannot exceed maximum energy consumption E_{max}.

$$E_{max}\geq E=\sum_{j=1}^{k}e_m=\sum_{j=1}^{k}\sum_{i=1}^{n}e_i\lambda_i \tag{21}$$

Only a part of the energy is used in machining process. A ratio between the energy consumption in machining process E_1 and the total energy consumption E is shown by formula (22). A constraint value E_a is set to ensure high efficiency of energy consumption.

$$\mathrm{E}_a \le \frac{E_1}{E} = \frac{\sum_{j=1}^{k} \mathrm{e}_1}{\sum_{j=1}^{k} \mathrm{e}_m} \tag{22}$$

Cost constraint: The total cost C should not exceed the highest cost C_{max}.

$$C_{max} \ge C = \sum_{i=1}^{n} \eta_i c_i \tag{23}$$

Machining quality constraint: The manufacturing quality Q must be higher than the lowest requirement of service application C_{min}.

$$\mathrm{Q}_{\min} \le Q = \sum_{i=1}^{n} \delta_i q_i \tag{24}$$

Material constraint: Material consumption of manufacturing service W should be no more than the highest material consumption W_{max}.

$$W_{max} \ge W = \sum_{i=1}^{n} \beta_i w_i \tag{25}$$

Energy and time consumption deviation constraint: There are many dynamic events which are possible to happen during manufacturing, such as new service request, delivery delay, delay of material, machine down time, etc. The dynamic events will affect the time and energy consumption of manufacturing equipments. Therefore, the scheduling of manufacturing services should be adaptive to these dynamic events. An energy and time consumption deviation constraint is set as a precondition to perform a rescheduling when the manufacturing is affected by dynamic events. Assume that the actual and expected energy and time consumption of manufacturing equipment r_m after finishing n tasks is (e,t) and (e',t') respectively, the rescheduling will be triggered when the deviation exceeds the threshold as shown by formula (26). This threshold is used to avoid frequent rescheduling and maintain the stability of manufacturing.

$$\Delta e \ge |e - e'| \ \mathrm{I} \ \Delta t \ge |t - t'| \tag{26}$$

5. Methods of Perception Data-Driven Optimization

5.1 Joint energy and production optimization driven by perception data

Data-driven rescheduling makes use of perception data which identify the dynamic changes in manufacturing. The process of perception data-driven dynamic scheduling of job shop manufacturing equipment services is shown by Fig.4. The production status, energy efficiency, and the productivity are perceived to identify the manufacturing equipment affected by dynamic changes. An energy and time deviation constraint shown by formula (26) is used to trigger the rescheduling.

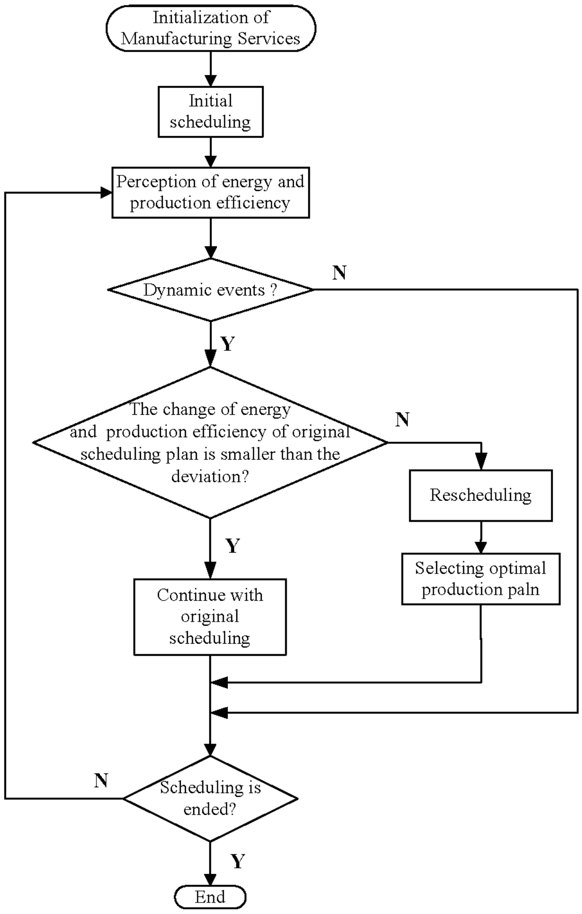

Fig.4 Perception data-driven dynamic scheduling of manufacturing equipment services

5.2 Bees algorithm for multi-objective optimization of manufacturing equipment services

Many heuristic algorithms have been used in the shop scheduling such as genetic algorithm (GA), simulated annealing algorithm (SA), particle swarm optimization algorithm (PSO), ant colony optimization algorithm (ACO). This paper uses an enhanced Pareto-based bees algorithm for the multi-objective dynamic scheduling of job shop equipment services based on perception data. The Bees Algorithm (BA) [37] proposed in 2005, including global search strategy and local neighborhood search strategy, is a population-based optimal algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution. Because it is simple and comprehensible, BA has a wide range of applications, such as combinatorial optimization problem, multi-objective optimization problem, and shows the advantages to solve complex optimization problems. Based on these, artificial bee colony algorithm (ABC) is proposed [38]. There are some scheduling studies using BA. Pan et al. presented a hybrid Pareto-based discrete artificial bee colony algorithm for solving the multi-objective flexible job shop scheduling problem [39]. Wang et al. proposed an enhanced Pareto-based artificial bee colony (EPABC) algorithm to solve the multi-objective flexible job-shop scheduling problem [40]. Li et al. proposed a novel discrete artificial bee colony (DABC) algorithm for solving the multi-objective flexible job shop scheduling problem with maintenance activities [41].

Due to the complexity of manufacturing service scheduling, it is difficult to solve the problem effectively with a single searching operator. This paper proposes an enhanced Pareto bees algorithm (EPBA) which fuses the initialization with multiple strategies, exploitation search procedures, crossover and mutation operators, fast non-dominated sorting, local depth search based on critical path, and recombination strategy in the framework of the BA algorithm. It emphasizes the balance of the global exploration and local exploitation, and the diversity of population during the searching process. Thus, it is adopted and expected to achieve good performances in solving the problem of manufacturing service scheduling.

5.2.1 The encoding, decoding and initializing representation

Job shop manufacturing equipment service scheduling problem can be abstracted into a flexible job-shop scheduling problem (FJSP). According to the FJSP, the solution encoding includes equipment services and service request encoded by the equipment service assignment vector and the service request sequence vector respectively. Suppose there are N service requests, each request has s_j tasks. The total number of tasks is $S=\sum_{j=1}^{N} s_j$. The coding length of equipment service and service request is the same. So the total coding length is $L=2S=2\sum_{j=1}^{N} s_j$. The operations of each service request are denoted by the corresponding service request number, and the i-th occurrence of a request number refers to the i-th operation in the sequence of this request. For the equipment service assignment vector, each number represents the equipment service assigned for each request successively.

For example, a coding sequence is $A=[1,2,3,4,2,3,1,4,3,1,4,2:5,6,7,8,7,6,8,5,6,8,7,5]$. The first half of A indicates the service request code, and the second half indicates the equipment service code. In the coding, there are 4 service requests (1,2,3,4) and 4 equipment services (5,6,7,8) as candidates, each request has three tasks, and is fulfilled in accordance with the coding sequence, the equipment services are arranged according to service request sequence and task number. For example, the three tasks of service request 1 and 2 separately use equipment services (5,6,7) and (8,7,6).

In the decoding process, we use the left-shift mechanism, which allows service request arranged as early as possible. Given an idle time $\Delta t=\left[t_k^{start},t_k^{end}\right]$ for equipment service k , and a time interval beginning from ST_{ij} and ending at CT_{ij} to fulfill the task O_{ij} of service request i on the equipment service k , the time ST_{ij} is determined by the ending time $CT_{i(j-1)}$ of previous task $O_{i(j-1)}$ and the idle time Δt of equipment service k . The starting time ST_{ij} can be described as $ST_{ij}=\max(t_k^{start},CT_{i(j-1)})\ and\ CT_{ij}\le t_k^{end}$, if t_k^{end} does not exist, it is considered as ∞. Finding all the idle time intervals $[\Delta t_1,\Delta t_2 \mathrm{L}\ \Delta t_n]$ on the machine k from left to right, if a time interval Δt_l satisfies the constraints, then this task can be started. Such a left-shift decoding scheme is used to allocate each task on its assigned equipment service from left to right following the sequence vector of the solution. Thus, it decodes a solution to a detailed schedule.

In order to guarantee the quality and diversity of an initial population, that is the equipment service assignments, we use six rules: (1) Random rule; (2) Local minimum processing time consumption rule; (3) Local minimum energy consumption rule; (4) Local maximum quality rule; (5) Local minimum cost rule; (6) Local minimum material consumption rule. In our algorithm, 25% of equipment service assignments are generated by rule 1, 15% by rule 2 to 6. After the equipment services are assigned, the service request operations will be sequenced. We apply three rules to generate initial operation sequences: (1) Random rule; (2) Most time remaining rule; (3) Most number of task operations remaining rule. 40% solutions are generated by rule 1, 30% by rule 2 to 3. Meanwhile, two archive set *AS* and *BS* are used to record the non-dominated solutions and searched critical paths.

5.2.2Scout bees operation

Each bee's position represents a solution of the optimization problem. The neighborhood searching area nearby a food source is known as the flower. For each food source S_i , a scout bee makes a random mutation operation and variable neighborhood search operation to get a new food source S_{new} . If S_{new} is better than S_i , S_{new} replaces S_i . Then the new scout bees population is ranked by fast non-dominated sorting to distinguish the merits of solutions.

(1) Random mutation operation

Learning from mutation operation of genetic algorithm, for a solution S_i , a position is randomly selected from the equipment service coding, and is replaced by a different equipment service randomly chosen from the candidate equipment service set. Two adjacent positions are randomly selected and exchanged from the service request coding to generate a new solution S_{new}. Then the S_{new} is evaluated. If S_{new} dominates S_i, replace S_i with S_{new}. If they have different objectives and do not dominate each other, then keep S_i while updating *AS* with S_{new}.

(2) Variable neighborhood searching

In the basic scheme, the neighborhood radius ngh is constant, but this paper uses a variable neighborhood radius to improve the flexibility. For a solution S_i, the integer *J* as the neighborhood radius ngh is randomly generated from 1 to S (total number of tasks), then *J* positions are randomly selected from the equipment service code, and are replaced by different equipment service randomly chosen from the candidate equipment service set. Then a new solution S_{new} is generated, and the radial distance of two solutions is $D = J$, and S_{new} is evaluated. If S_{new} dominates S_i, replace S_i with S_{new}. If they have different objectives and do not dominate each other, then keep S_i while updating *AS* with S_{new}.

For a solution S_i, an integer *I* is randomly generated from 2 to (N-1) (N is total number of service requests), *I* service request numbers are randomly selected, and the positions of selected numbers are found in the service request code. Then the positions of selected numbers are sequentially replaced by different service request randomly chosen from *I* service request set, and a new solution S_{new} is generated. The radial distance of two solutions therefore is $D = \sum_{i=1}^{I} L_i$, and S_{new} is evaluated. If S_{new} dominates S_i, replace S_i with S_{new}. If they have different objectives and do not dominate each other, then keep S_i while updating *AS* with S_{new}.

(3) Fast non-dominated sorting

In order to quickly identify non-dominated individuals and improve sorting speed, this paper uses pre-sorting and quick sorting strategies: First, population S is pre-sorted, according to the value of the first objective. If the value of the first objective of some solutions are the same, the value of the second objective are adopted, if the value of the first and second objectives of some solutions are the same, the value of the third objective are adopted, and so forth to get pre-sorted population $S_a = \{s_1, s_2 \ldots s_n\}$. Then, population S_a is quickly sorted, population S_a is copied as $S_b = S_a$, the second solution s_2 of S_b is selected and compared with other solutions. A new population $S_b^{'} = \{s_{i,} s_{j,} \ldots s_k\}$ is grouped by the solutions from S_b, which dominates s_2 or does not dominate each other. Similarly, the second solution s_j of $S_b^{'}$ is selected and a new population is grouped by the solutions from $S_b^{'}$, which dominates s_j or does not dominate each other. And so forth, the fast non-dominated sorting does not complete until the last non-dominated solution is found.

5.2.3 Recruit bees operation

In the specified neighborhood radius, recruited bees do depth neighborhood search based on the critical path, while adaptive variable neighborhood search strategy and crossover and mutation strategy are used to improve search efficiency.

(1) Recruit bees population selecting

In the basic BA algorithm, bees choose a food source based on the fitness value, and the selected probability is higher when the food source fitness is greater. But the fitness is indeterminate in the multi-objective problem. In this paper, each recruit bee chooses a food source according to the rank of non-dominated sorting, and the selected probability is higher when the rank is smaller. Given the number of food sources *A*, the maximum rank of non-dominated sorting K, the food sources with rank from 1 to K/2 are the selected bees $m+e$, the food sources with rank 1 are the best bees e, the food sources with rank from K/2 to K are the remaining bees $A-e-m$, number of recruit bees for the best *e* sites is $nep = 4\times e$, number of bees recruited for the other m selected sites is $nsp = 2\times m$, recruit bees for the remaining bees are randomly selected from $A-e-m$, then the recruit bees population P_t is formed.

(2) Adaptive variable neighborhood searching

Recruit bees are made an adaptive variable neighborhood search, which is executed as variable neighborhood search in the scout bees operation, but the size of neighborhood search radius ngh adapts to the rank of non-dominated sorting K, $ngh = {}^{J}\!/_{K}$ (*J* is a random integer). The greater the neighborhood radius is, the better recruit bees are, and the quality and diversity of bee population will be improved.

(3) Crossover and mutation operation

Learning from crossover and mutation operation of genetic algorithm, a random mutation operation is executed on recruit bees, which is used in the scout bees operation. Crossover operator is designed for recruit bees to exchange information to increase the diversity of individuals. For each solution generated by the recruit bee S_i using the exploration search, another solution S' is randomly selected from *AS* with probability P_a or from the population with probability $1-P_a$.

The crossover operators for equipment service coding and service request coding are developed as follows: For equipment service coding, a 0-1 string with the same length of equipment service coding is randomly generated. If one position of 0-1 string is 1, the same position of new solution inherits the code from S_i. If not, it inherits the code from S', as shown in Fig.5. For service request coding, an integer *K* is randomly generated from 1 to (N-1) (N is total number of service request), then *K* service requests are randomly selected and compose a service subset J_s. If one service request belongs to the subset J_s, the new solution is filled by the service's number in the same positions from S_i. If not, the new solution is sequentially filled the service number from S', shown in Fig.6.

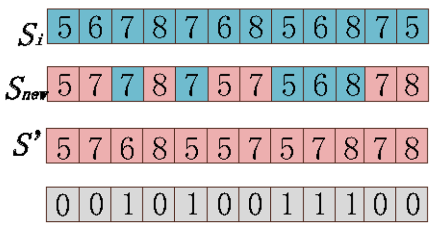

Fig.5 Manufacturing equipment service code cross

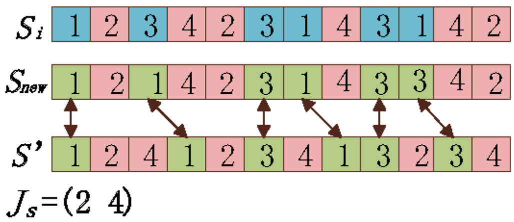

Fig.6 Service request code cross

(4) Local depth search based on the critical path

Job shop manufacturing equipment service scheduling can be described by directed graph $G=[N,A,E]$, where *N* represents the task set after service requests are decomposed, *A* represents the relations of task set, *E* represents the sequence of equipment services. As shown in Fig.7, there is a directed graph of job shop manufacturing equipment service scheduling with 4 service requests. *S* and *T* represent the initial service set and the completed service set respectively. The time consumption of every task is marked out. From *S* to *T*, a service subset $G_{\max}$ with the highest time consumption is called critical path length, which equals the completion time of the whole job shop manufacturing equipment service. In Fig.7, the critical path is shown by bold red, and all steps in the critical path are critical step, including (O_{21},M8,0-5), (O_{31},M8,6-10), (O_{41},M8,11-12), (O_{42},M7,13-14), (O_{13},M7,15-18). Since the completion time is no shorter than any possible critical path, it can be improved only by moving the critical steps.

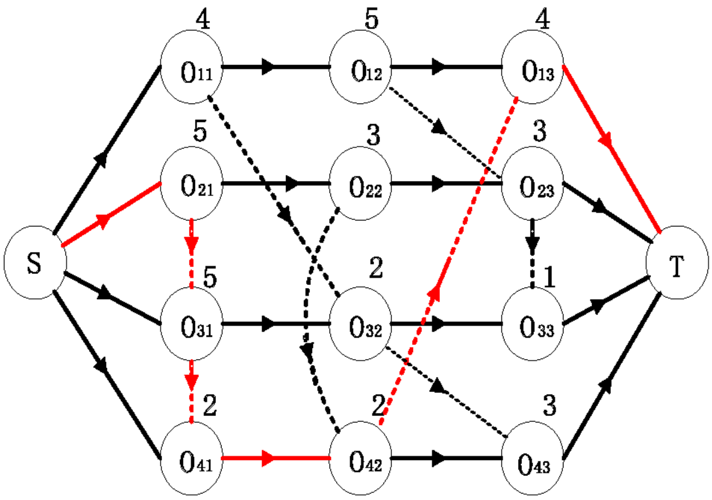

Fig.7 Example of manufacturing equipment service scheduling in job shop

In the local depth search based on the critical path, the new solution is obtained by moving critical steps, and neighborhood radius equals to the length of the critical path. Since large amounts of data need to be operated, depth local search probability is set as P_L <1 in order to compromise quality and efficiency of searching. There are two ways to move critical steps, as follows: (1) If the number (*N)* of candidate equipment services of a critical step is $N > 1$, the critical step is assigned different equipment service; (2) If the number (*M)* of tasks of a critical equipment service is assigned $M > 1$, the order of the two adjacent tasks are exchanged. When the critical paths are not unique, the common parts of these critical paths need to be moved since some tasks are completed at the same time. All the solutions obtained by moving critical path of old ones are sorted by fast non-dominated sorting. If they are not dominated by each other while having different objectives, then it updates archive set *AS* with the new one. If there are some new solutions dominate the old one, one of them will be selected and replace the old one. As there may be different solutions with the same critical path, this will cause unnecessary duplicate search. If a critical path has been searched, it will update the critical path taboos set *BS*. For the next solution, if the critical path has been concentrated in the *BS*, it does not need local depth search. By using the local depth search for the temporary population P_t, a new population Q_t is generated.

(5) Population Recombination

To improve the population quality, the following recombination strategy is used. First, populations P_t and Q_t are combined into QP_t, and duplicate individuals in it are removed. Then, all the solutions are sorted by using the fast nondominated sorting, and the solutions in the best front and subject to the constraints are used to update *AS*. Last, P_{size} (number of population size) solutions are selected from the best front to the worst one and form a new population.

5.2.4Algorithmic flow

As mentioned, the framework of the proposed EPBA algorithm is illustrated in Fig. 8.

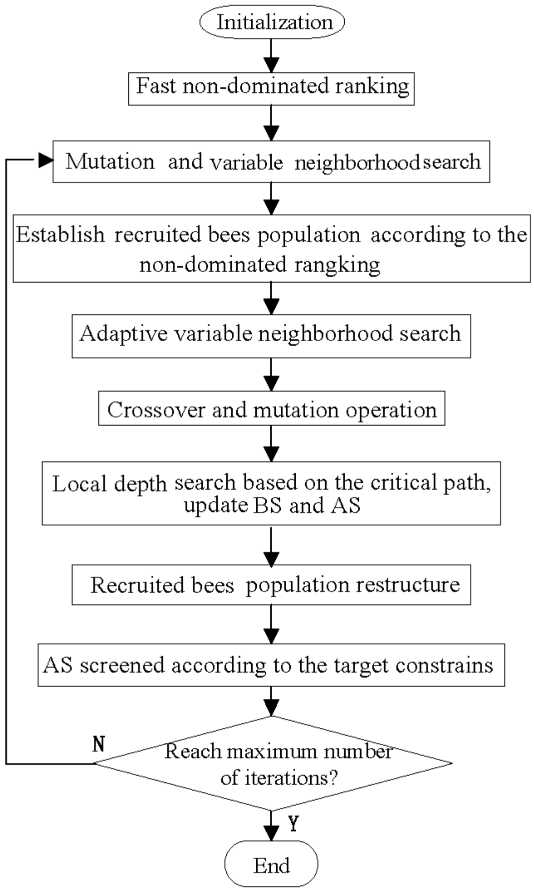

Fig.8 Flowchart of bees algorithm for equipment service scheduling

6. Performance Evaluation

The test environment and parameter settings are given in Table 1, including initial population size (P_S), maximum number of iterations (Gen_{max}), the probability to perform the local depth search (P_L), and the probability of crossover operator (P_a). There are two parts in the test: (1) three-objectives optimization with Kacem [42] instances, (2) five-objectives optimization for job shop manufacturing equipment service scheduling.

6.1 Algorithm simulation and performance test based on Kacem

To test the performance of the proposed EPBA algorithm, four Kacem [42] instances are carried out with three objectives C_M, W_T, and W_M. EPBA are compared with the existing algorithms including PSO+SA [43]、PSO+TS [44]、HTSA [45]、P-DABC [46]、EPABC [40]、DABC [41]. The results are listed in Table 2, where the results of the existing algorithms are obtained from literatures. From Table 2, it can be seen that EPBA is one of the best algorithms for solving the four Kacem instances. The nondominated solutions of EPBA are more than that of PSO+SA, PSO+TS, HTSA, and P-DABC. It means EPBA is an effective algorithm.

6.2 Example of static service scheduling

A platform of manufacturing equipment service scheduling is taken as an example. There are 10 manufacturing equipments and 6 requests. Every request consists of 6 tasks. So there are a total of 36 tasks. Matched equipment *J* is selected from equipment service platform. The number *J*, time consumption *T* (minute), energy consumption *E* (KWh), product quality *Q*, cost *C* (hundred yuan), and material consumption *W* (hundred yuan) for each task are list in Table 3 as *J/T/E/Q/C/W*. The objective of the service scheduling is to achieve optimal *T*, *E*, *Q*, *C* and *W*. The constraints of the scheduling problem are shown in Table 4.

EPBA adopted in this paper is compared with Pareto Genetic Algorithm (PGA), Pareto artificial bee colony (PABC), Weighted

Bees Algorithm (WBA). The parameter settings are shown in Table 5, where P_m is the mutation probability, P_c is the crossover probability. Fig.9 shows the average number of non-dominated solution of 10 experiments. The optimal solution of WBA is 1 or even 0 under strict constraints. There are more optimal solutions of PABC and PGA which adopt Pareto domination sorting. The optimal solutions of EPBA are the most among all the algorithms in the experiments. This will give more choices for equipment service scheduling.

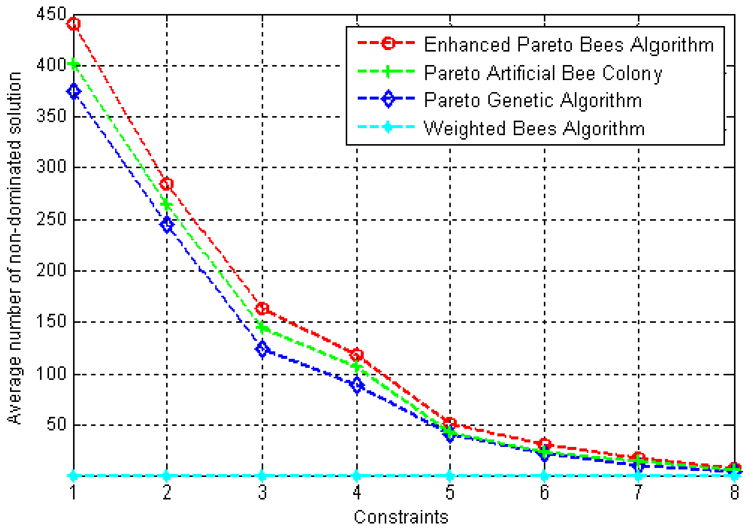

Fig.9 Number of optimal solution under different constraints

Assume that the Pareto solution set is *SP*. The Pareto set of EPBA is *SK*. The three indicators proposed for DABC [41], namely minimum average distance form *SK* to *SP* D< which is the shorter the better, the average number of non-dominated solutions N< which is the larger the better, and the ratio of non-dominated solutions R< which is the higher the better, are adopted to evaluate the results of EPBA. Table 6 shows the indicators after 10 experiments. It can be seen from Table 6 that EPBA shows the best performance.

Fig.10, Fig.11, and Fig.12 show the D<, N<, and R< versus number of iterations respectively. Generally, the distance of each algorithm between *SP* and *SK* of each algorithm decreases and converges to a stable state. There is a temporary increase of D< of each algorithm. This is because some inferior solutions are added to the Pareto solution set. As shown in Figure 11 and 12, EPBA generates more optimal solutions and non-dominated solutions than PABC and PGA.

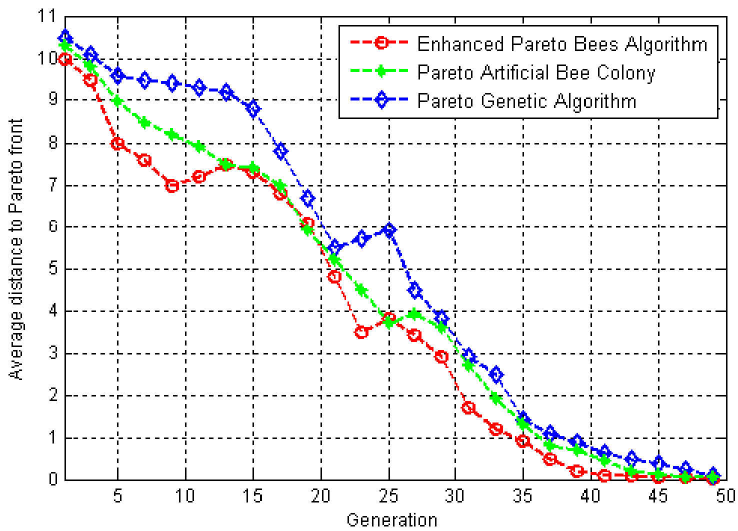

Fig.10 Average minimum distance D<

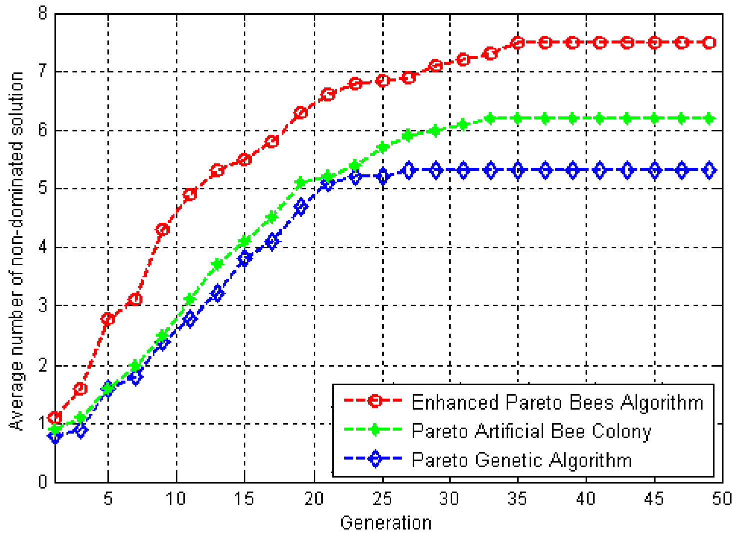

Fig.11 Average non-dominated solution N<

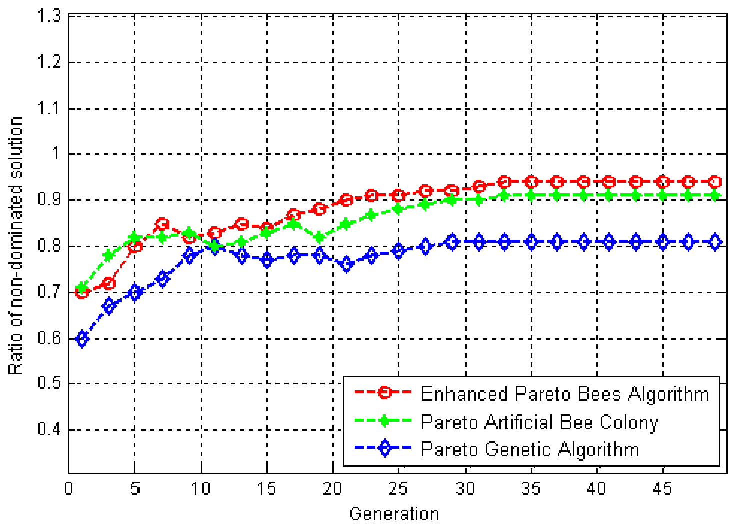

Fig.12 Ratio of non-dominated R<

The result of manufacturing equipment service scheduling by using EPBA is shown in Fig.13. T=49, E=168 KWh, Q^{-1}= 9.0302, C=143.7 hundred yuan, W=123.5 hundred yuan. The tasks of every service request are shown by blocks in the same colour. The first digit of the numbers in the blocks means the number of service requests. The second one has no meaning and is a space character. The third one means the number of tasks.

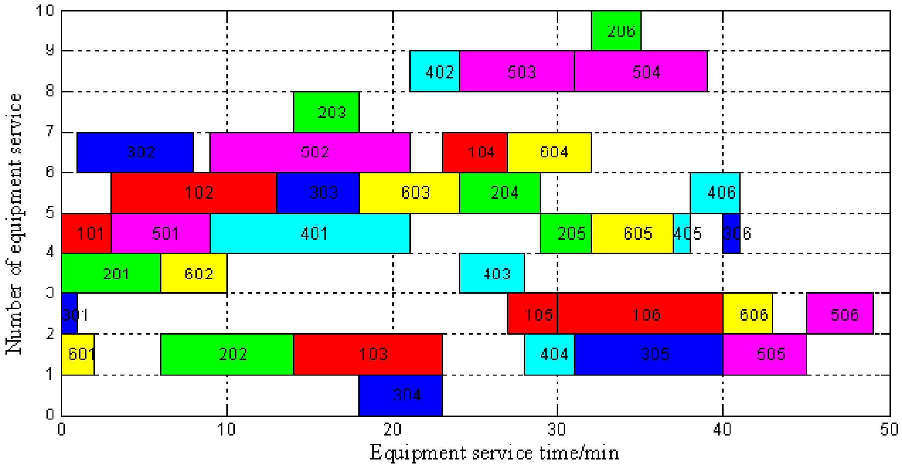

Fig.13 An optimal scheduling Gantt chart

To summarize the results of static scheduling, EPBA gives more optimal solutions than PGA, PABC, and WBA. EPBA also shows the best performance in minimum average distance, average number of non-dominated solutions, and ratio of non-dominated solutions among these algorithms.

6.3 Example of dynamic service scheduling

Three events are used to test the dynamic performance of the service scheduling for energy and production optimization: (1) A new service request 7 is added to the current production plan at time *T*=5. The service request 7 contains 3 tasks. The manufacturing equipments and their corresponding capability are listed as *J/T/E/Q/C/W* in Table 7; (2) The cutting tool of the manufacturing equipment 2 should be replaced at time *T*= 6, and the task 2 of service request 2 will be delayed for 6 minute; (3) The task 2 of service request 3 is not completed properly by manufacturing equipment 7 and needs to be redone. The corresponding *T, E, Q, C, W* of manufacturing equipment 7 will be affected and changes from 7/4/4/5.5/3 to 10/6/4/7/4. The threshold of energy and production deviation is shown in Table 8.

For the first event, a new scheduling will be carried out at time *T* = 6. At time *T* = 6, equipments 6 and 7 are assigned to task 2 of request 1 and task 2 of request 3 respectively. The rescheduling problem can be seen as scheduling with constraints of unavailable time of manufacturing equipment. Fig.14 and Table 9 show the results of rescheduling. It can be seen that the total time consumption *T* is not affected by the dynamic event. *E, Q, C*, and *W* increase very slightly.

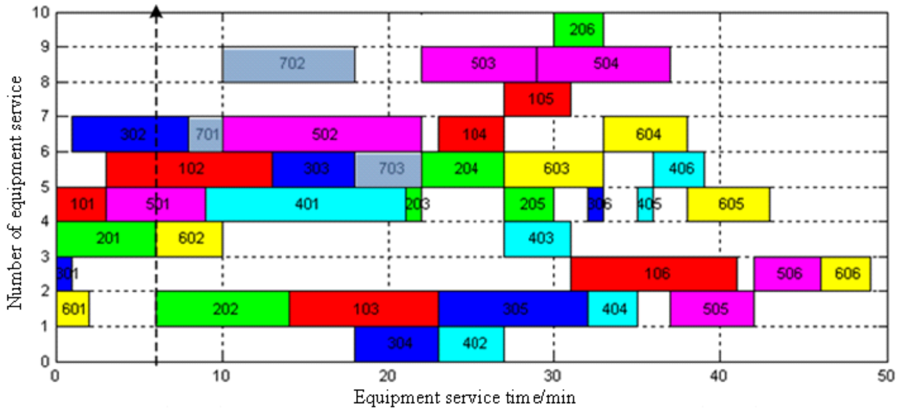

Fig.14 Dynamic scheduling with new service request

For the second event, the cutting tool of the manufacturing equipment 2 should be replaced at time *T*= 6. The task 2 of service request 2 is delayed for 6 minute and finished in 14 minutes. Therefore, the corresponding *T, E, Q, C, W* of manufacturing equipment 2 will change from 8/7/7/6/5 to 14/7/7/6/5. It is calculated that *T* will be 53 if a rescheduling is not performed, and the time deviation *ΔT* will be greater than the threshold in Table 8. The change of energy and production efficiency will be monitored by sensors and triggers the rescheduling. The rescheduling will be performed then and the total time consumption is 51 minutes which is smaller than 53 minutes. The changes caused by dynamic scheduling are shown in Fig.15 and Table 10.

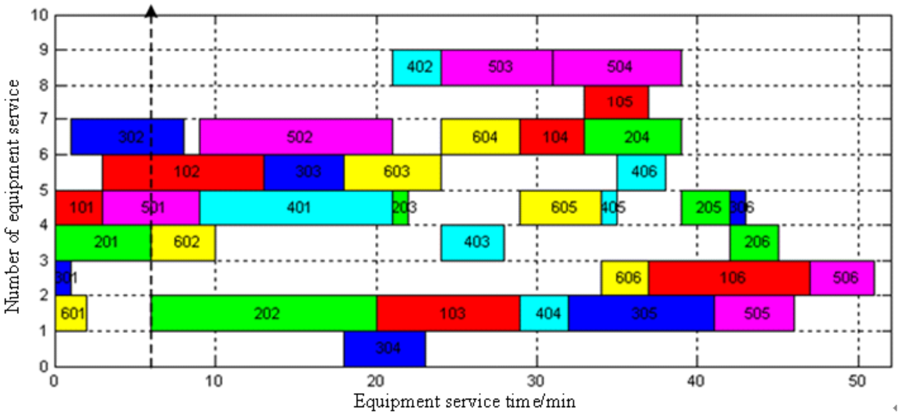

Fig.15 Dynamic scheduling with tool replacement

For the third event, the task 2 of service request 3 should be redone when *T* = 8. The time consumption will increase from 7 minutes to 10 minutes, the energy consumption will increase from 4 KWh to 6 KWh, the cost will increase from 5.5 hundred yuan to 7 hundred yuan, the material consumption will increase from 3 hundred yuan to 4 hundred yuan, and the quality will decrease from 4 to 3. If the rescheduling is not triggered, the total energy consumption will be 170 KWh, and the cost will be 145.2 hundred yuan. The energy and production deviation exceeds the threshold and a dynamic rescheduling will be triggered. The results of the dynamic scheduling are shown in Fig.16 and Table 11 and are within the threshold.

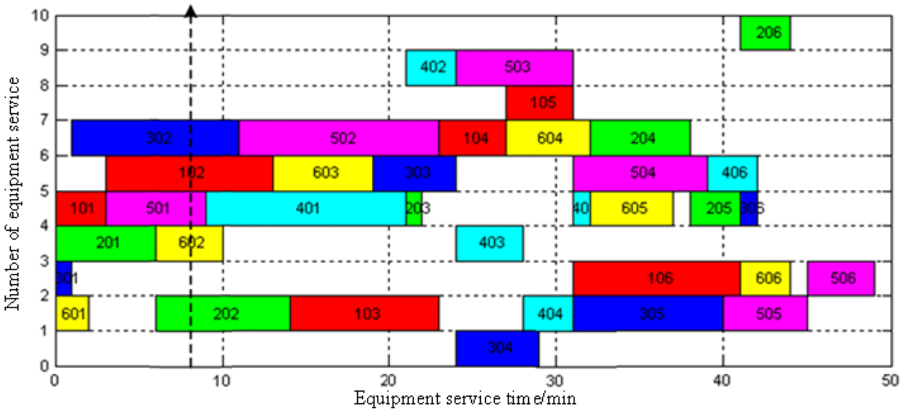

Fig.16 Dynamic scheduling with failure

It can be seen from the dynamic scheduling that the energy and production efficiency will be increased obviously compared with the original production plan. Data-driven method is the base of the rescheduling. The threshold will reduce frequent influence on the manufacturing process and keep the production process stable.

7. Conclusions

In this paper, job shop manufacturing equipments are encapsulated into manufacturing services, so the users can use equipment resources at any time according to their needs. This enhances the flexibility of job shop production and improves the response speed and production efficiency. This paper proposes a sustainable scheduling optimization of manufacturing equipment services based on joint energy and production model. The scheduling is driven by perceived real-time energy and production efficiency information. Some kinds of dynamic events are introduced and the dynamic scheduling is performed to respond to these events. The conclusions of this paper are as follows:

(1) Joint energy and production model of job shop is established. The model considers the time consumption, the energy consumption, the quality of product, the cost, and the material consumption. This is a comprehensive joint energy and production model of job shop and lays a solid foundation for sustainable scheduling optimization of manufacturing equipment services.

(2) A multi-objective optimization algorithm EPBA is proposed to generate optimal production plan to improve energy and production efficiency. EPBA adopts strategies such as adaptive variable neighborhood search, local depth search based on the critical path, crossover and mutation operators, fast non-dominated sorting, and local depth search to improve the efficiency of the algorithm and avoid premature convergence. The performance of EPBA is compared with other algorithms and achieves better performance.

(3) Data-driven dynamic scheduling of job shop manufacturing equipment services is put forward. A deviation threshold strategy is taken to avoid frequent changes of production plan. The simulation results show that data-driven dynamic scheduling of job shop manufacturing equipment services is feasible and capable to improve the energy and production efficiency of production.

Dynamic scheduling optimization of manufacturing services is very complex. In this paper, in order to simplify the model and reduce the difficulty, the scheduling only considers limited factors. Further research will be carried out from the following aspects: establish a more comprehensive model for sustainable manufacturing by considering society influence of manufacturing; considering the different energy efficiency of different states of machine; studying other kinds of uncertain events such as machine faults.

Acknowledgements

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