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Real-time Production and Logistics Self-adaption Scheduling based on Information Entropy Theory

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Abstract: In recent years, the individualized demand of customers brings small batches and diversification of orders towards enterprises. The application of enabling technologies in factory, such as the Industrial Internet of Things (IIoT) and Cloud Manufacturing (CMfg), enhances the ability of customer requirement automatic elicitation and the manufacturing process control. The job shop scheduling problem with random job arrival time dramatically increases the difficulty in process management. Thus, how to collaboratively schedule the production and logistics resources in the shop floor is very challenging, and it has a fundamental and practical significance of achieving the competitiveness for an enterprise. To address this issue, the real-time model of production and logistics resources is built firstly. Then, the task entropy model is built based on the task information. Finally, the real-time self-adaption collaboration of production and logistics resources is realized. The proposed algorithm is carried out based on a practical case to evaluate its effectiveness. Experimental results show that our proposed algorithm outperforms three existing algorithms.

Keywords: industrial internet of things; random job arrival time; information entropy theory; self-adaption; real-time scheduling

1. Introduction

With the growing demand for product customization, the characteristic of orders is developing towards diversification and small batch. Usually, manufacturers' goal is to minimize the completion time and energy consumption. The factory arranges the manufacturing task according to its own goal, which rarely considers customers' requirements [1]. The scheduling problem with random orders has been becoming increasingly important for smart manufacturing. Traditionally, the manufacturing factory focuses on reducing production cost [2]. However, the goal of smart factory involves not only minimizing manufacturing cost, but also maximizing customer satisfaction.

In addition, manufacturers delivery delay will lead to reducing customer satisfaction and increasing costs. Under the Cloud Manufacturing (CMfg) mode, each customer wants to receive the required products from a smart factory within an expected date [3]. The manufacturers shall meet the customer's delivery time while considering their own production capacity limitations. Traditional scheduling assumes that information on production resources and tasks is fully known. This assumption is not applicable in a customized environment because customer orders will arrive dynamically [4]. In the intelligent plant, the instantaneity demand of customers dramatically increases the difficulty of job shop scheduling (JSP), i.e., random job arrival increases the complexity of scheduling problems [5].

In a new manufacturing environment, such as the Internet of Things and CMfg, tasks of smart shop floor (SSF) are ordered by a cloud platform, even by customers directly [6]. When the production and logistics resources are confronted with orders with random arrival and different due date, the traditional scheduling methods will be difficult to cope with such a new manufacturing scenario. In

the smart workshop, the coordination of production and logistics resources, as well as the random arrival time of orders and different due date, should be considered. Multi-resource collaboration and resources matching optimization are vital problems that need to be solved by the smart manufacturing system in a dynamic environment based on real-time serviceability.

Production and logistics\manufacturing resources (PLRs\MRs) collaborative scheduling is the basis for improving production efficiency and resolving the problem of insufficient production resources caused by the diversified needs of customers. However, there is little guidance about how production and logistics resources collaboration allocation affects the production decision of the remanufacturing system, especially in the real-time manufacturing system. In reality, production and processing are main stages that consume resources and energy, as well as the critical nodes with the most significant potential for intelligence. Hence, this phenomenon raises some questions. How should manufacture enterprises manage heterogeneous production and logistics resources to realize intelligence in manufacturing? Under the uncertain environment, how should the manufacturing system dynamically allocate real-time tasks?

This paper proposes a production and logistics real-time adaptive scheduling method based on information entropy to solve the above problems. The real-time scheduling method includes three parts. (1) It builds a real-time state model of production and logistics resources for dynamic production tasks based on real-time data of SFF; (2) It builds a standard entropy model of real-time tasks according to execution status and delivery time of customized orders; (3) Based on the standard entropy model of tasks and the real-time state model of resources, an Real-Time Scheduling algorithm based on Information Entropy Theory (RTSIET) is constructed for improving the efficiency of producer services.

Main contributions of this study are summarized as follows:

(1) RTSIET strategy based on adaptive coordination of smart resources can effectively deal with tasks with time constraints. It includes features that are rarely mentioned before, such as the allocate service resources according to due data.

(2) The adaptive scheduling strategy reduces production time, energy consumption and delays through the optimization of feasible services. Besides, compared with traditional scheduling strategies, RTSIET strategy developed in this paper can improve coordination ability among PLRs and enhance the stability of real-time scheduling.

The remaining of this paper is organized as follows. Section 2 gives a literature review. Section 3 describes the problem of RTMRA with scenario description. Section 4 presents the conceptual model and the information model. Section 5 describes the overall solution and fundamental algorithms for RTMRA. Based on a practical case, Section 6 represents and analyzes the research results of this paper. Section 7 highlights the conclusions and provides future works.

2. Rlated Work

The flexible job shop scheduling problem (FJSP) is an outgrowth of the classic job shop scheduling problem (JSP), which has multi-function machines [7]. During the past three decades, there has been extensive development of efficient techniques for solving the FJSP in the traditional manufacturing industry [8]. Evolutionary algorithms (EAs), such as particle swarm optimization (PSO) algorithm [9] and fireworks algorithm (FWA) [10], show advantages in solving optimization problems. Some popular EAs, such as PSO, FWA, genetic algorithm and so on, which are applied to traditional FJSP, have achieved excellent results [11,12]. Although researchers have tackled the JSP with various brilliant approaches, there are limitations when dealing with practical implementation under an ever-changing modern environment where a real-time scheduling decision is required due to unpredictable systems disturbances at any seconds [13].

The production of Smart Flexible Job Shop (SFJS) with distinct due window of multi-customer increases the difficulty of job shop scheduling. Hence, traditional flexible job shop scheduling methods are difficult to adapt to new conditions. As a kind of data-driven knowledge model, the manufacturing resource allocation (MRA) model is of critical importance in the manufacturing industry, which determines the efficiency and flexibility of a shop floor and its production system

[14]. Smart manufacturing resources, e.g. machines, vehicles and Work in Process (WIP), in SFJS have self-configuration, self-learning, and self-decision intelligence [15,16].

In the environment of Industrial Internet of Things (IIoT), real-time manufacturing resources allocation (RTMRA) can be further developed to make full use of the interconnection among manufacturing resources to achieve intelligent cooperations [17]. Therefore, it is timely and crucial to consider adaptive scheduling and control (i.e., RTMRA) for dynamic manufacturing environments as crucial research issues in smart production management [18]. The timely feedback shop floor information during the manufacturing execution stage leads to significant improvement in achieving real-time production scheduling [19]. Luo et al. [20,21] proposed to integrate wired and wireless networks by also taking advantage of the automated guided vehicle (AGV) in smart factories, which increases data delivery efficiency. Zhang et al. [22] presented an overall architecture of multi-agent-based real-time production scheduling to close the loop of production planning and control. Shiue et al. [23] proposed reinforcement learning (RL)-based RTS using the multiple dispatching rules mechanism to respond to changes in the shop floor environment. Ding et al. [15] trained a hidden Markov model (HMM)-based knowledge model from the historical data for smart manufacturing resources (SMRs) to allocate themselves autonomously for manufacturing tasks. Zhang and Wang [24,25] proposed an allocation strategy based on game optimization model for real-time tasks. Both production resources (PRs) and logistics resources (LRs) in smart shop floor(SSF) are created as an inseparable whole, yet majority of scheduling research focused on one of them and only took the other as constraint condition, even without any consideration [26]. [27] and [28] used a discrete firefly algorithm to solve one of the most common multicriteria decision making problems. [29] proposed a framework for SFF based on a cyber-physical system and agent model of manufacturing resources. Masoud et al. [30] discussesed the effect of real-time data on the efficiency of production logistics system. Azadian et al. [31] studied the operation problem of combining production scheduling with transportation planning to improve the efficiency of operation.

Pareto front is an important concept of multi-objective optimization problems [32]. Scholars have done a lot of research on the near-complete Pareto front of problems [9,10]. However, the current research focuses on the implementation of real-time production and logistics scheduling, and lacks of research on scheduling results[33]. Furthermore, the above methods and technologies ignore the information properties of real-time tasks. Making full use of the information properties of resources and tasks in SFF is the premise and foundation of realizing intelligent manufacturing.

3. Problem Description and Mathematical Model

3.1. Problem Description

As shown in Figure 1, there are three main roles, i.e., customers, CMfg platform and SSF, in this scenario. As service demanders, customers submit orders requirements to the CMfg platform. CMfg platform decomposes orders and gets real-time jobs (i.e., product components). An SSF receives real-time manufacturing jobs, and further decomposes jobs and gets real-time tasks (i.e., manufacturing tasks), according to the real-time orders information, real-time status information of resources in SSF and product process requirements. Then, SSF obtains logistics tasks according to the production and logistics cooperative strategy. As service providers, production and logistics equipment receive allocated manufacturing and logistics tasks and execute these tasks according to task schedules. Finally, the completed products are delivered to the service demander through logistics from the selected service provider.

The real-time allocation problem is the matching problem between manufacturing resources (including PRs and LRs) and manufacturing tasks with specific process requirements according to their status [14]. Different from the traditional scheduling problem, RTMSA problem of multi-resource collaboration considers heterogeneity and dynamics of SMRs, as well as the utility efficiency and sustainability of environmental impact in the manufacturing system operation stage. In addition, the influence of customer behavior on satisfaction degree is also considered.

The RTMRA can be stated as follows. Given a set of jobs $job_{set} = \{job^k | k = 1,2,\cdots,K\}$, a set of AGVs $A = \{a_i | i = 1,2,\cdots,I\}$ and a set of machines $M = \{m_j | j = 1,2,\cdots,J\}$. Each job has two time attributes, i.e., arrive time and due date. In addition, if a job is completed after the due date, the tardiness penalty cost is generated. The aim of RTMRA is to provide an adaptive task allocation strategy so that multiple objectives are optimized simultaneously. Assumptions are given as follows [5,34,35]:

1. Jobs arrive randomly, and jobs have a different due date.
2. Each operation may be executed on a set of alternative machines.
3. The arrival time and due date of a job is not known until the job arrives.
4. Each machine can perform only one ordinary job processing at a time.
5. Transportation time of AGVs is considered.
6. A task, once taken up for processing on a machine, should be completed before another task is taken.
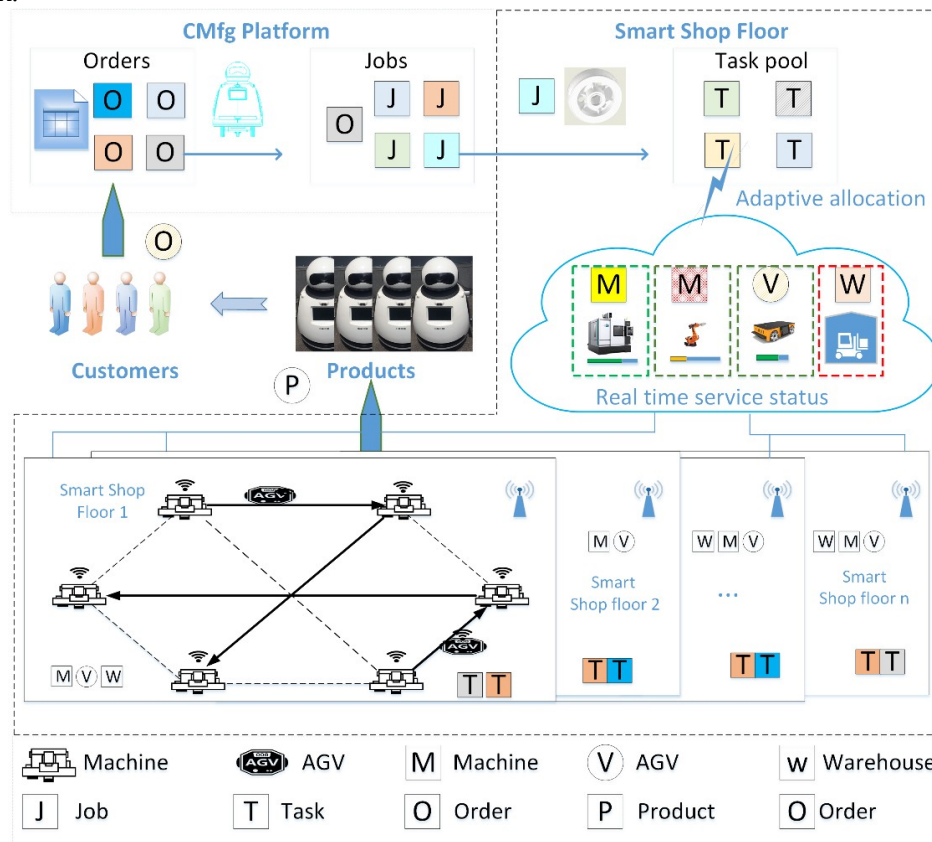

Figure 1. Scenario description of RTMSA problem

3.2. Mathematical Model

To facilitate reading and understanding, Table 1 lists the mathematical symbols used in this article.

In SSF, reducing the average task delay time of all tasks is a key scheduling optimization objective [3]. The mathematical model for RTMRA can be defined as follows. In this model, the studied objectives include makespan, total energy consumption and mean tardiness.

$$F = min\{f_1, f_2, f_3\} \tag{1}$$

$$f_1 = max\{C^k\} \tag{2}$$

$$f_2 = \sum_{k=1}^{d} \sum_{j=1}^{m} p_{nj}^k + pp_{ni}^k \times \sum_{k=1}^{d} \sum_{j=1}^{v} p_{ni}^k + \sum_{j=1}^{m} I_j \times p_j^I \tag{3}$$

$$f_3 = \frac{1}{d} \times \sum_{k=1}^{d} L^k \tag{4}$$

S.t.

$$ \tag{5}$$

$$L^k = max(0, C^k - d^k)$$

$$i = \{1,2,\cdots,I\} \tag{6}$$

$$j = \{1,2,\cdots,J\} \tag{7}$$

$$n = \{1,2,\cdots,N\} \tag{8}$$

In this mathematical model, f_1 denotes the makespan; f_2 denotes the total energy consumption, which includes energy consumption of machine and energy consumption of AGVs; f_3 denotes mean tardiness of jobs.

Table 1. The notation used in the study

Notations	Description
job_{set}	Job set
job^k	k-th job
tk_n^k	n-th operation of job k, $job^k = (tk_n^k \mid n = 1,2,\cdots,l)$
s_j^t	Type of service that a machine can provide
pp_{nj}^k	Power of m_j for the operation of tk_n^k
p_{nj}^k	Service time of m_j for tk_n^k
pp_{ni}^k	Power of the AGV i for the operation of tk_n^k
p_{ni}^k	Service time of the AGV a_i for tk_n^k
bp_{nj}^k	The time when the machine starts to the operation of tk_n^k
fp_{nj}^k	Completion time for tk_n^k
bp_{ni}^k	Start time of a_i to operate tk_n^k
mp_{ni}^k	The time AGV arrives at the machine where the tk_n^k is located
fp_{ni}^k	The time of a_i completes the tk_n^k
p_j^I	Idle power of m_j
$\bar{v}$	Speed of an AGV
L_i	Location of a_i
$\bar{m}_j^t$	Capacity of m_j at time t
$\bar{a}_i^t$	Handling capacity of a_i at time t
$\bar{M}$	Optional machine set
$\bar{A}$	Optional AGV set
Tk^t	A set of tasks in the task-pool
sq_j	Service queue of m_j
I_j	Total idle time of m_j
sq_i	Service queue of AGV a_i
C^k	Completion time of job^k
d^k	Due date for job^k
L^k	Lateness of job^k

4. Model Description in Smart Shop Floor

4.1. Conceptual Model

The objects of data acquisition are manufacturing resources in smart factories, such as machines, AGVs, WIP, etc. Under IIoT environment, the internal producing department can obtain real-time data in time by industrial bus, wireless sensor network, RFID reader and camera, etc. The external

can obtain real-time orders by industrial cloud platform, ERP\MES and other upper-layer applications. The dynamic characteristics of workshop resource status and order arrival time require the smart workshop resource model to differ from the traditional one [36]. The production resource service model of smart workshops should not only built its static serviceability, but also have the function of constructing real-time service capability based on its own real-time state and task requirements.

Definition 1-Smart Work-in-progress (SWIP). It refers to goods in process with passive recognition ability in physical space. SWIP can be perceived by manufacturing resources (e.g. manufacturing equipment, processing equipment and people) in the manufacturing environment and read, related requirements (e.g. production process, emergency grade and deadline) of SWIP. Manufacturing resources are dynamically adjusted in the manufacturing process to coordinate the completion of production tasks.

Definition 2-Smart Manufacturing Resources (SMRs). It refers to production process based on WIP complete the relevant handling, processing (assembly) and quality inspection and other related resources, including production resources, logistics resources, and people with wearable devices that are capable of sensing, communication interaction, learning, execution, self-control, etc., in physical space. After establishing the business association, smart manufacturing resources and SWIP jointly complete the manufacturing task in the form of cooperation/competition with the goal of the lowest manufacturing cost, the highest manufacturing efficiency and the lowest energy consumption.

Smart modeling matrix set of PRs includes two parts: the attribute of resources and real-time status in the environment of IIoT. Real-time status includes dynamic queue, service load and service process status, etc. Hence, the real-time perception of the state of key manufacturing resources in smart workshops is the basis of constructing the smart model [37]. The purpose of introducing SWIP and SMRS into the self-adaption scheduling process is to formalize product requirements, resource capabilities, attributes and constraints.

In order to manage the real-time state data of key resources more effectively, the real-time state model of PRs (e.g. machines and numerical control machining centers) and LRs (e.g. AGVs) are constructed as follows:

At time t, the set of services types of m_j can be described as $S_j^t = \{s_j^\alpha | \alpha = 1,2,\cdots,\theta\}$, where θ is the number of service types that m_j can be provided, and s_j^α is one of them. Meanwhile, the set of services types of m_j can be described as $S_i^t = \{s_i^\tau | \tau = 1,2,\cdots,\gamma\}$, where γ is the number of service types that a_i can be provided, and s_i^τ is one of them.

The real-time status attribute of production equipment has six characteristics, including equipment number, service option, manufacturing energy consumption, idle energy consumption and manufacturing time.

$$\bar{m}_j^t = \left(m_j, S_j^t, ep_{nj}^k, e_j^I, p_{nj}^k, sq_j\right) \tag{9}$$

where S_j^t denotes the type of service that the machine can provide, ep_{nj}^k denotes the processing energy consumption of the machine tool for the current task, e_j^I denotes the idle energy consumption of the machine too, p_{nj}^k denotes the service time of the machine tool for the current task, sq_j denotes the service queue of m_j.

The real-time status attribute of logistics equipment is defined as seven characteristics, including equipment number, service options, location of the handling equipment, handling energy consumption, standby energy consumption and handling time.

$$\bar{a}_i^t = \left(a_i, S_i^t, L_i, ep_{ni}^k, e_i^I, p_{ni}^k, sq_i\right) \tag{10}$$

where S_i^t denotes the type of service provided by the handling equipment a_i, L_i denotes the energy consumption of the handling equipment for the task, ep_{ni}^k denotes the location of the handling equipment, e_i^I denotes the idle energy consumption, p_{ni}^k denotes the service time of the handling equipment for the current task, sq_i denotes the service queue of a_i.

Definition 3 -Real-time Tasks (RTs). Generally, in the field of manufacturing, there are two types of tasks, i.e., simple tasks and complex tasks. A simple task is a basic task that can be completed independently by a single service resource. It is a definite step of a complex task. Simple tasks have positive input conditions and output results. In addition, it also contains explicit attribute features,

such as task arrival and end time, resource capability demand and task execution time, etc. In this paper, RTs refer to complex tasks. It contains two simple tasks, such as production task of tk_n^k and logistics task of tk_n^k.

The production and logistics collaborative manufacturing scenario in SSF, a manufacturing task includes a production task and a logistic task [38]. In this study, the production task and logistics task of a manufacturing task are packaged and released in groups. We assume that task tk_n^k will be performed by m_j and a_i. Hence, the input set of tk_n^k is denoted by (11).

$$Input = \left(tk_n^k, \bar{m}_j^t, \bar{a}_i^t\right) \tag{11}$$

where, $\bar{m}_j^t$ is the status of the machine m_j which will be performing the production task of tk_n^k, $\bar{a}_i^t$ is the status of the AGV a_i which will be performing the logistics task of tk_n^k. It describes the serviceability of required before tk_n^k execute at time t, including the ability of processing resources and the ability of logistics resources.

When the task is completed at time $\check{t}$, the output set of the tk_n^k is denoted by (12).

$$Output = \left(tk_{n+1}^k, \bar{m}_j^{\check{t}}, \bar{a}_i^{\check{t}}\right) \tag{12}$$

It describes the status of service resources when tk_n^k has been executed at time $\check{t}$.

4.2. Real-time Information Model of Tasks for Multi-customer

Entropy is defined as the product of information generated by an event and the probability of the event [26]. In the scenario described in Section 3, this paper focuses on orders with different arrival time and due date. In a real-time distributed system, remaining execution time and deadline are some fundamental attributes of real-time tasks that elucidate the activities of the manufacturing system [34].

In the intelligent workshop layer, we can easily obtain the real-time process of jobs and the real-time status of PLs based on the Conceptual model. We assume that the release time of tk_n^k is time t, $tk_n^k \in job^k$. The predicted mean remaining processing time of job^k is denoted by (13).

$$rp\_tk_n^k = \sum_{i=n}^{I} \sum_{c=1}^{r} \frac{p_{nj}^k}{r} \tag{13}$$

where l is the total process number of job^k; r is the number of optional machines in each process (task) of job^k.

We assume that task tk_{n-1}^k is processed on the machine m_j, and task tk_n^k will be processed on the machine m_j. The distance between the machine m_j and the machine m_j is denoted by $Dist(m_j, m_j)$. The predicted mean remaining delivery distance of job^k is denoted by (14).

$$d_n^k = \frac{1}{J} \sum_{j=1}^{J} Dist(m_j, m_j) + \frac{(l-n-1)}{J^2} \sum_{j=1}^{J} \sum_{j=1}^{J} Dist(m_j, m_j) \tag{14}$$

where, $\hat{j}, j, \check{j} \in [1, m]$, $\frac{1}{J} \sum_{j=1}^{J} Dist(m_j, m_j)$ is the predicted mean remaining delivery time of tk_n^k, $\frac{(l-n-1)}{J^2} \sum_{j=1}^{J} \sum_{j=1}^{J} Dist(m_j, m_j)$ is the predicted mean remaining delivery time from tk_{n+1}^k to tk_J^k.

The predicted mean remaining service time of job^k is denoted by (15).

$$rpl\_tk_n^k = rp\_tk_n^k + rl\_tk_n^k \tag{15}$$

where $rl\_tk_n^k$ represents the predicted mean remaining delivery time of job^k, i.e., $rl\_tk_n^k = \frac{d_n^k}{\bar{v}}$.

Due to each task has its due date, at time t, the remaining completion time of tk_n^k is denoted by (16).

$$rc\_tk_n^k = d^k - t \tag{16}$$

Subject to the constraints in formulas (13) to (16), we apply the information-theoretic concepts to define the following parameters [39–31]:

The urgency of task $U(tk_n^k)$ is the probability of execution of the task by the ratio between the predicted mean remaining service time $(rpl\_tk_n^k)$ and the remaining completion time $(rc\_tk_n^k)$ of the task. At time t, the urgency of tk_n^k is denoted by (17).

$$U(tk_n^k) = \frac{rpl\_tk_n^k}{rc\_tk_n^k} \tag{17}$$

Normalized urgency of a task is the probability of a task normalized by the sum of all the tasks' urgency. We assume that the total number of the tasks in task-pool at time t is x. The tasks in task-pool can be described as tk_n^{kb}, where $b \in [1, x]$. Normalized urgency of a task in task-pool at time t, denoted by (18).

$$NU(tk_n^{kb}) = \frac{U(tk_n^{kb})}{\sum_{b=1}^{x} U(tk_n^{kb})} \tag{19}$$

where, $NU(tk_n^k) = NU(tk_n^{kb})$ at time t.

The urgency of the task is a vital attribute under an uncertain scheduling environment. We define this attribute as standard entropy of tk_n^k, which is formulated as

$$NE(tk_n^k) = -\log_2 NU(tk_n^k) \tag{20}$$

5. The Proposed Method

Two characteristics of customers' dynamic demands are considered in this paper, namely arrive time and due date of orders. In order to handle dynamic customer demand, a PLRs adaptive scheduling method is proposed. Fig. 2 displays the flowchart of the PLRs adaptive scheduling method. The real-time scheduling method consists of two key parts, i.e., task trigger rules and entropy-based scheduling strategy.
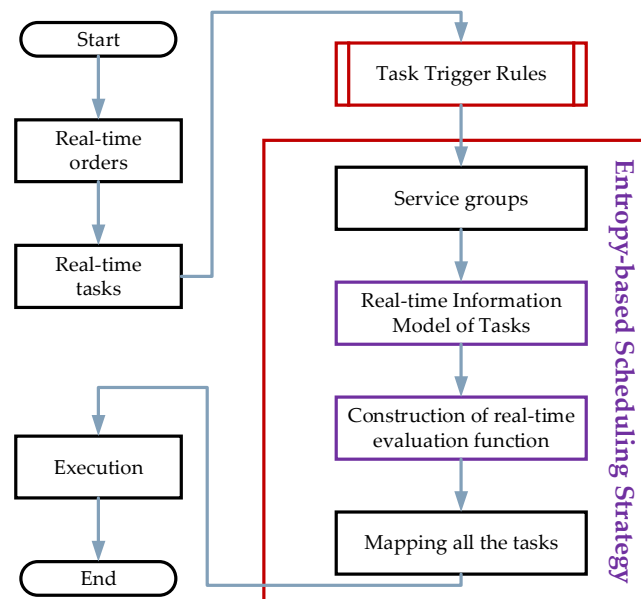

Figure 2. The flowchart of PLRs adaptive scheduling.

5.1. Task Trigger Rules

Task triggering consists of three steps. The first one is at the beginning of execution when jobs are released from the cloud to the job pool in the SSF. SSF should divide jobs into tasks according to the production process. Then the first task of the job is put into the task-pool, a set of tasks in the task-pool denoted as Tk^t. For example, tk_1^k is put into the task-pool at the beginning. Tasks in task-pool will trigger the entropy-based scheduling strategy. Then, in the middle of execution, when tk_n^k is successfully allocated, tk_n^k will be deleted and tk_{n+1}^k will be added to the task-pool. Finally, the above steps are repeated until the last task of the job is processed.

5.2. Entropy-based Scheduling Strategy

When the scheduling policy is triggered, the scheduling center can query optional machines and optional AGVs according to task type. We will get the optional production resources set $\bar{M}$ and optional logistics resources set $\bar{A}$. The set of the status of $\bar{M}$ and the set of the status of $\bar{A}$ can be denoted by $\bar{M}^t$ and $\bar{A}^t$. In this paper, all the machines are NC machining centers, all of them have multiple kinds of capabilities, and all of the AGVs are the same type of equipment (It is noteworthy that all AGVs have the same speed, power and types of service). Therefore, $\bar{M}^t = \{\bar{m}_j^t | j = 1,2,\cdots J\}$ and $\bar{A}^t = \{\bar{a}_i^t | i = 1,2,\cdots I\}$.

In that way, G_U is the service groups set to meet the service requirements of tasks in task-pool at time t, denoted by (21).

$$G_U = \{(a_i, m_j) | a_i \in \bar{V}, m_j \in \bar{M}\} \tag{21}$$

Assume that g_y is one service group of the G_U, $G_U = \{g_y | y = 1,2,\dots,U\}$ and $g_y = (a_i, m_j)$, where, $U = I \times J$. Suppose that the tk_{n-1}^k is processed on the machine m_j, tk_n^k will be processed on the machine m_j. Suppose that AGV a_i provides logistics services to tk_n^k, L_i is the location of v_i when it starts to execute the logistics task of tk_n^k. The distance between L_i and the machine m_j is denoted by $Dist(m_j, L_i)$. The pick-up time cost of AGV for tk_n^k is denoted by $p_{nij}^k = \frac{Dist(m_j, L_i)}{\bar{v}}$, the delivery time cost of AGV for tk_n^k is denoted by $d_{nij}^k = \frac{Dist(m_j, m_j)}{\bar{v}}$.

Fabricating costs of WIP, include raw material cost, time cost and production energy consumption. The cost of raw material is the inherent cost of manufacturing, and it will not be changed by scheduling. Time cost includes manufacturing time and handling time. The manufacturing time depends on the serviceability of the equipment arranged for the process production, which will change due to different production scheduling. The handling time depends on the service capacity of equipment (all AGVs have the same speed and energy consumption, so it is only the difference of pick-up time\delivery time caused by the different location of AGV), and the position of the working procedure before and after the work in WIP, which will change due to the different scheduling. Hence, the total service time of service group g_y is denoted by (22).

$$T_y = p_{nj}^k + p_{nij}^k + d_{nij}^k + max(bp_{ni}^k - fp_{nj}^k, 0) + max(bp_{nj}^k - fp_{ni}^k, 0) \tag{22}$$

where, $max(bp_{ni}^k - fp_{nj}^k, 0)$ is waiting time of AGV i to pick up the WIP (tk_n^k), $max(bp_{nj}^k - fp_{ni}^k, 0)$ is the waiting time of the WIP (tk_n^k) to be executed.

Suppose that tk_n^k is processed before tk_n^k on machine m_j. The total energy consumption of service groups g_y is denoted by (23).

$$W_y = bp_{ni}^k \times (p_{nij}^k + d_{nij}^k) + p_{nj}^k \times ep_{nj}^k + max(bp_{ni}^k - fp_{nj}^k, 0) \times e_j^I \tag{23}$$

Compared with global scheduling, the advantage of real-time scheduling is that it can deal with high-frequency disturbances, but its short-sightedness makes it difficult to obtain the global optimal solution. Accordingly, it is very hard to control the completion time of each job. The weight method can get better results through repeated simulation. In the real world, the situation is unpredictable. In high-disturbance real-time scheduling, it is very difficult to obtain excellent scheduling results with fixed weight method.

SFF is characterized by high disturbance, i.e., real-time tasks. Compared with single scheduling rules, combined scheduling rules can improve the production capacity of the workshop.

This paper proposes an adaptive weight method based on information entropy. Therefore, we can build the function f_0 as the real-time evaluation function.

$$f_0 = \omega_e \times T_{normalization} + (1 - \omega_e) \times W_{normalization} \tag{24}$$

S.t.

$$\omega_e = 1 - NE(tk_n^k) \tag{25}$$

$$T_{normalization} = \frac{T_y - T_{min}}{T_{max} - T_{min}} \tag{26}$$

$$W_{normalization} = \frac{W_y - W_{min}}{W_{max} - W_{min}} \tag{27}$$

where, T_{min} is the minimum service time of the optional composite service, T_{max} is the maximum service time of the optional composite service, W_{min} is the minimum energy consumption of the optional composite service, W_{max} is the maximum energy consumption of the optional composite service.

The goal of our research is to schedule the tasks in the task-pool, at a given point in time. We use f_0 to judge service quality of service groups, and select the service group with the lowest total cost. According to the pairing result of the service groups and the tasks in the task-pool, all tasks are assigned to the optimal machines and AGVs.

In the IIoT environment, tasks may be located at different geographical locations, and the service groups supporting these tasks are complicated and heterogeneous. Without loss of generality, we use the symbol r_{ny}^k denote the allocation relationship between the task and service group g_y. After mapping all the tasks in task-pool to service groups, the result of the real-time schedule can be written as:

$$r_{ny}^k : tk_n^k \xrightarrow[allocation]{} g_y \tag{28}$$

where, Tk^t is a set of tasks in task-pool at time t, $tk_n^k \in Tk^t$.

Using information entropy to balance the preference between service time and energy consumption for task allocation. It can effectively avoid the disadvantages of fixed weight method. Moreover, the proposed method can effectively control the order completion time in real-time scheduling. Based on previous studies, a real-time scheduling algorithm based on information entropy theory (RTSIET) is proposed. RTSIET is briefly described in **Algorithm 1**.

Algorithm 1 Real-time scheduling algorithm based on information entropy theory

Input: Tk^t, t, d^k, $\bar{M}^t$, $\bar{A}^t$

Output: $r_{ny}^k : tk_n^k \xrightarrow[allocation]{} g_y$

While (*taskpool* ==! null) **do**

 for tk_n^k in *taskpool*

  Compute the standard entropy for each task in *taskpool*

  as formula (19)

  for g_y in G_k **do**

   Compute service quality of each groups and chose

    the best one using (24)

  end for

 end for

end while

---

6. Case Study

To conduct the experiment evaluation, we adopt a practical case from a medium robot manufacturing company located in Wuhan, China. There are multiple NC Machining Workshops in Wuhan. The rapidly developed market of online shopping in China caused the increased demand of personalized products like robots. Companies have to offer customized services to suit the needs of customers.

In this section, a demonstrative case from a robot manufacturing enterprise of Wuhan has demonstrated the feasibility of the proposed model for RTMSA. Flexible production and logistics resources with randomly arrival jobs are considered.

6.1. Case Description

As shown in Figure 3. It is a layout of Hub workshop, which is a workshop of robot manufacturer. There are six machines, one automated warehouse and some AGVs are involved in the shop-floor.
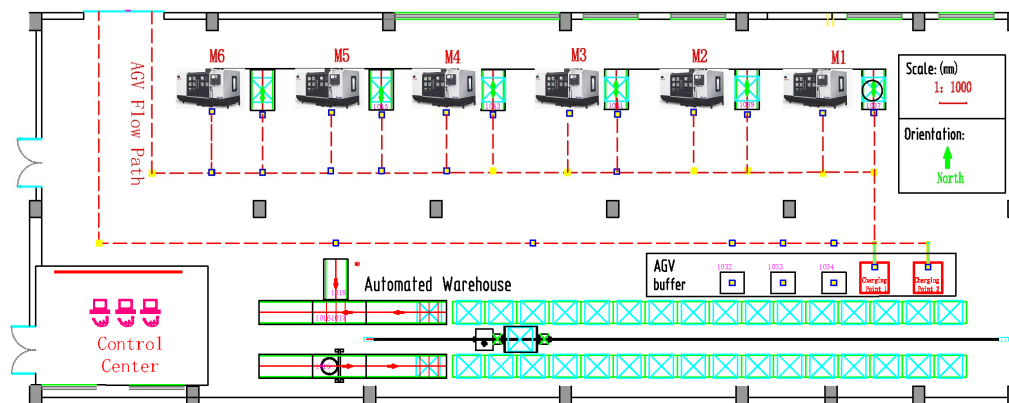

Figure 3. The layout of Hub workshop.

The distances among the warehouse and machines are shown in Table 2.

Table 2. The distance among the warehouse and machines.

$(m_0$ is warehouse, $m_1 \sim m_6$ are machines.$)$

Distance [m]	m_0	m_1	m_2	m_3	m_4	m_5	m_6
m_0	0	40	46	52	60	66	75
m_1	40	0	6	12	16	24	33
m_2	46	6	0	12	18	24	33
m_3	52	12	6	0	6	12	21
m_4	60	18	12	6	0	6	15
m_5	66	24	18	12	6	0	9
m_6	75	33	27	21	15	9	0

Table 3. The distance between the warehouse and each machine.

Time[s]\Power[kW/h]		m_0	m_1	m_2	m_3	m_4	m_5	m_6
	1CT	180\3.74	190\3.11	170\4.38	180\4.24	190\3.41	200\4.5	180\3.74
	2TU	170\4.38	190\4.11	170\4.48	170\4.59	180\4.24	200\3.95	170\4.38
job	3GR	170\4.06	190\3.18	170\3.70	170\4.08	180\5.82	200\4.08	170\4.06
	4DR	230\4.18	240\4.13	250\3.20	230\4.19	240\4.09	200\5.01	230\4.18
	5TA	220\5.40	220\5.39	240\4.17	230\5.28	240\4.68	260\4.57	220\5.40

Table 4. Idle power of machines.

m_i	m_0	m_1	m_2	m_3	m_4	m_5	m_6
Idle Power[kW/h]	0.98	1.23	1.48	1.06	1.06	1.16	1.27

In the SSF as described in this section, one hub is a job. Each job can be completed through a specific sequence of production processes. One production process type refers to a task type. There are five types of tasks in the manufacturing process: Cutting (CT), Turning (TU), Grinding (GR), Drilling (DR) and Tapping (TA). As a service provider, there is six different processing equipment (CNC machines). Each machine can provide five different types of services. Each machine can execute manufacturing tasks with different service time expectations. The service time and power of machines are shown in Table 3.

In dynamic job shops, the distribution of jobs arrival process closely follows a Poisson distribution. Hence, the time between job arrivals closely follows an Exponential distribution [5]. According to the historical data of customer's orders, the probability distribution of order arrival is analyzed. Poisson distribution is used to describe the random arrival orders in the SSF. Suppose 15 jobs random arrive in 30 minutes. The job arrivals rate λ is equal to 0.5 respectively. Each job contains two attributes of time: arrival time and due date, denoted by $\overline{job^k} = (a^k, d^k)$. The relationship between order arrival time and due date is denoted by $d^k = a^k + \bar{c}$ [5]. According to the production data of the enterprise in three months, the average operation time of the jobs is 2000 seconds in Hub workshop, therefore, $\bar{c} = 2000s$.

The idle energy consumption of the machine is shown in Table 4.

The idle energy consumption of AGV is 0 because the communication cost is not considered in this paper. The speed and handling power of AGVs are shown in Table 5.

Table 5. Power\Speed of AGVs.

AGV	a_i
Power[kW/h]	1
Speed[m/s]	0.5

The proposed method has been performed in python language on a computer with Intel I7 4710MQ CPU 2.5 GHz processor and 8.00 GB memory.

6.2. Results of Experiments

In order to illustrate the potential of the proposed method for the multi-objective dynamic JSP, it is compared with Self-Adaptive Collaboration Method (SCM) [33] and some common dispatching rules. A combination decision model of scheduling rules such as the longest processing time (LPT) dispatching rule, the shortest processing time (SPT) dispatching rule and the first in first out (FIFO) dispatching rule [5].

Paper [33] views each resource (machine and AGV) in the job shop as an active entity to request the production tasks. The processing and logistics tasks will be allocated to the optimal resources according to their real-time status by using weight method. This method only considers the real-time status of resources but does not fully consider the value engineering information such as random arrival jobs. Therefore, sometimes the resources allocation may not be suitable, thereby reducing the efficiency of the production system. Compared with the above research, which stands at the viewpoint of real-time job shop multi-resource self-organization in the production execution stage, our model stands at the viewpoint of real-time job shop multi-resource self-adaption for autonomous allocation of SPLA in both production execution and customer requirements stage.

According to the case study, series of experiments are conducted in order to evaluate the contribution of the adaptive weight mechanism based on entropy to the performance method. Table 6 contains average and standard deviation values for makespan, energy consumption and mean tardiness obtained across 200 runs on each instance with different number of AGVs. With the increase of the number of AGVs, the indexes of all methods are improved. It can be easily found from Table 8 that the proposed method has the potential to achieve the optimal solutions. It also can be found in that mean and variance of makespan, total energy consumption and mean tardiness of the proposed method are best among all the methods. Furthermore, it can also be seen that the SPT performs better than the SCM, and the SCM performs better than the LPT. This is mainly because compared with the SCM model, FIFO+SPT has a powerful predilection of time minimization, which can handle complex relationships between more objectives, thus resulting in relatively better performance. However, the powerful predilection of time maximum of FIFO+LPT is hard to deal with the interaction between multiple objectives, thus resulting in the worst performance. These results illustrate that the proposed method performs better among all the methods, and it can improve the performance of the scheduling system by keeping the schedule stability and the schedule efficiency simultaneously when the jobs arrival at random.

According to the above analysis, we can observe that FIFO+LPT performs the worst. Therefore we will not cover it in this study. Figure 4 intuitively shows the three-dimensional Pareto fronts obtained by three algorithms (i.e., RTSIET, FIFO+SPT and SCM) with five AGVs in solving the problem. It is clear that the non-dominated solutions obtained by RTSIET get closer to the coordinate origin. In most cases, the solutions of SCM and FIFO+SPT are scattered, which means that SMC and FIFO+SPT are challenging to obtain better results stably. It implies the superiority of RTSIET compared with other algorithms in solving the proposed problem.

Table 6. Results compare with RTSIET, SCM, FIFO+LPT and FIFO+SPT.

NA	RTSIET						SCM					
	C_{max}[s]		E[10000J]		$\bar{T}$[s]		C_{max}[s]		E[10000J]		$\bar{T}$[s]	
	MV	V	MV	V	MV	V	MV	V	MV	V	MV	V
1	3898	179	7857	101	108	5	5881	2893	8763	1558	1932	143
2	3135	55	7416	102	0	0	5328	2661	8195	1259	1518	118
3	3040	72	7281	95	0	0	5266	2741	8089	1314	1346	122
4	2989	53	7204	101	0	0	5197	2723	8014	1328	1234	124
5	2975	51	7165	90	0	0	5202	2695	7978	1221	1004	117

NA	FIFO+LPT						FIFO+SPT					
	C_{max}[100s]		E[100000J]		$\bar{T}$[100s]		C_{max}[s]		E[10000J]		$\bar{T}$[s]	
	MV	V	MV	V	MV	V	MV	V	MV	V	MV	V
1	193	4.20	1840	37.5	197	6.37	3918	157	8201	127	1149	927
2	192	4.17	1828	36.4	196	6.36	3559	82	7873	121	965	411
3	190	3.56	1812	31.1	193	5.54	3498	71	7777	115	784	351
4	187	3.03	1787	27.8	190	4.88	3509	73	7769	110	965	363
5	188	2.94	1736	34.4	181	3.69	3639	79	7761	991	857	371

Notes: NA represents the number of AGVs; E represents total energy consumption; $\bar{T}$ represents mean tardiness; C_{max} represents makespan; MV represents mean value; V represents variance.
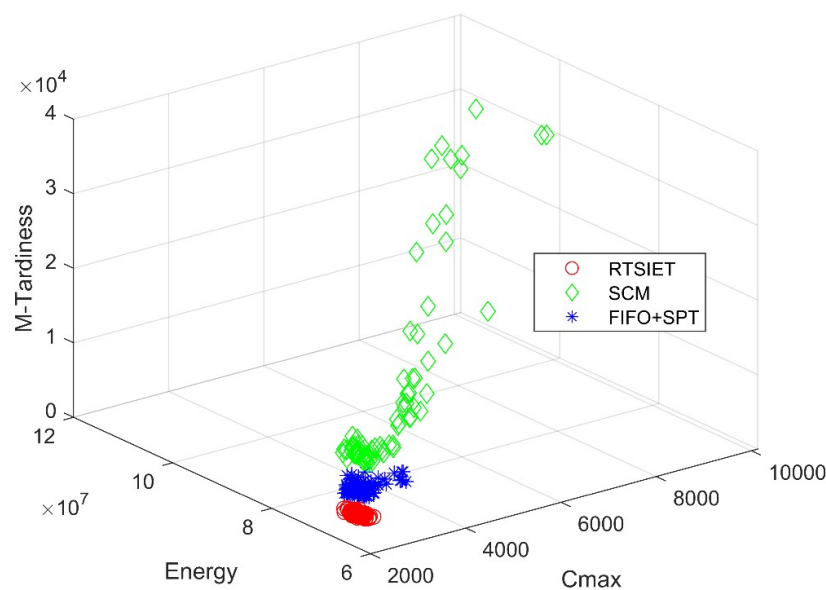

Figure 4. Pareto front of three algorithms in solving the proposed problem.

In order to verify the universality and effectiveness of the proposed method, we have also done simulation verification on other production workshops (e.g. bearing support workshop and assembly workshop). Compared with other methods, the stability and effectiveness of the proposed method are still the best. Because in the high disturbance production environment, the adaptive scheduling strategy based on information entropy can well balance time and energy consumption. The balance characteristics of the proposed method has extraordinary significance for intelligent workshops: (1) A good scheduling method can not only improve customer satisfaction and reduce production costs, but also reduce the interference of human factors through replacing some of the functions of workshop manager. (2) The stability and excellent scheduling results of the adaptive scheduling strategy prove that the proposed method is an effective method to realize intelligent unmanned workshop.

7. Conclusions

This paper focuses on the enterprise's manufacturing decisions by considering high disturbance environment. A real-time status model of heterogeneous resources in SSF is established. The mathematical model is formulated with three objectives, i.e., the makespan, energy consumption and mean tardiness of jobs. A Real-Time Scheduling algorithm based on Information Entropy Theory (RTSIET) based on the dynamic service capability of manufacturing resources is proposed. Then, a real-world case is employed to explore scheduling method in a high disturbance and multi-resource environment. In addition, the algorithm performance under random arrival jobs is analyzed. The proposed model is solved by RTSIET, which can obtain the real-time multi-objective weight value by calculating the standard information entropy of each job. The agility and stability of the system are demonstrated through practical application.

We will apply this real-time scheduling strategy to a combination of other method in our future research. The game theory may be a good candidate due to its multi-resource collaboration ability.

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