Graduation Intelligent Manufacturing System for Advanced Planning and Scheduling in PI-enabled Hyperconnected Fixed-Position Assembly Islands

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Abstract: *The inherent complexity and uncertainty of planning and scheduling problems in production management have plagued researchers and practitioners for decades, especially when confronted with more diversified customer demand, fast-changing supply chain and market. Physical Internet (PI) enabled manufacturing shows the potential to revolutionize the way production and operations are managed and done in factories. Massive production data and information are real-timely accessible for decision-makers thanks to the application of various frontier sensing, networking, and computing technologies in PI. Thus, it is imperative to study how to leverage the strengths of real-time data and information to support production planning and scheduling in PI-enabled manufacturing environment. This paper proposes a five-phase framework of the Graduation Intelligent Manufacturing System (GiMS) to facilitate decision-making in the PI-enabled fixed-position assembly islands. GiMS divides space and time scopes of a factory into finite areas and intervals to minimize complexity and approximate uncertainty, so that the original monolithic planning and scheduling decision can be discretized into a series of real-time decisions. Shop floor status is established and updated in real-time through PI-enabled visibility, traceability, and hyperconnectivity. Synchronization mechanisms of GiMS are designed to provide globally optimized and locally resilient solutions. Finally, a numerical study is carried out. The results show that GiMS has a well-balanced and stable performance on several measures in a dynamic environment.*

Keywords: *Graduation Intelligent Manufacturing System (GiMS), Advanced planning and scheduling, PI-enabled manufacturing, Synchronization*

1 Introduction

The layout of fixed-position assembly islands (FPAI) is commonly found in fragile and bulky equipment production such as aircraft, rotary printing presses, and lifts (Guo et al., 2020b). The FPAI consists of several assembly islands. Operators move from one island to another to perform specific operations. The product usually remains at one island for its entire assembly process to reduce costs and avoid potential damage in the movement, while the required components and equipment are moved to the island according to the assembly plan. Thus, there is no need to consider the traditional assembly line balancing problem in FPAI (Zeltzer et al., 2017). However, the increasing customized demand, inappropriate assembly islands configuration, frequent setups, and long waiting times complicate the production and operations management (planning, scheduling, execution, and control) in FPAI. Moreover, sophisticated assembly operations, multiple production resources movements (e.g., parts, tools) are error-prone so that the stochastic nature is further amplified.

Considerable attention has been devoted to addressing the production complexity and uncertainty from both industry and academia. Leading manufacturers and practitioners have developed a wide variety of advanced manufacturing systems such as enterprise resource planning (ERP) systems and manufacturing execution systems (MES) to generate production plans and schedules (Stratman, 2007). The usefulness of these systems is widely appreciated, but they are gradually becoming insufficient to meet the current customer demand with mixed production volumes and increasing product variety. Moreover, it is hard for using these systems to respond to the disturbances and uncertain issues in actual production progress without utilizing real-time shop floor data promptly (Land, 2009). Besides, frequent rescheduling may cause resistance to change, which might be counterproductive in improving production efficiency (Rahmani & Ramezanian, 2016). Then again, some manufacturers invested massively to build highly automated production lines. Still, the performance fails to come up to expectations because automation is perfect for executing static schedules with its preciseness and efficiency. However, automation alone is not smart enough to deal with various uncertainties in a nowadays dynamic and stochastic production environment; effective coordination and synchronization are indispensable (Yang et al., 2019).

On the other hand, researchers have tried a large variety of methods and algorithms to solve the APS problems mathematically and computationally. These approaches have produced more or less similar results that were theoretically optimal or near-optimal, but their performance in practice is unstable because the uncertainties are not well tackled. Afterward, hierarchical and production planning and scheduling (HPPS) and multi-period production planning and scheduling with rolling horizons (MPRH) have emerged. HPPS and MPRH are two typical "divide and conquer" approaches to locate and manage complexity and uncertainty. HPPS decomposes a complex problem into small size subproblems while MPRH discretizes the planning horizon into multiple short time intervals with manageable uncertainty (Campbell, 1992; Hax & Meal, 1973). However, both MPRH and HPPS require but suffer from the lack of feedback and updating mechanisms to integrate subproblems (McKay et al., 1995; Omar & Teo, 2007).

Fortunately, the Physical Internet (PI) enabled manufacturing shows tremendous potential in revolutionizing the way production and operations are managed and done in factories (Lin et al., 2018a). PI was first mentioned in the domain of logistics (Markillie, 2006) and has now been widely used for transforming logistics management worldwide. Recently, the concept of PI is extended to the manufacturing shop floor where cutting-edge technologies such as Industrial Internet-of-Things (IIoT), Cloud Computing (CC), Digital Twin (DT) are deployed (Zhong et al., 2017a). These disruptive technologies promise to upgrade the traditional manufacturing objects to smart objects augmented with identification, sensing, and network capabilities (Luo et al., 2019b; Zhong et al., 2017b). Real-time data and information are accessible. The connectivity, visibility, and traceability of the PI-enabled manufacturing environment bring new hope to break the bottleneck of complexity and uncertainty in production and operations management. To achieve real-time advanced planning and scheduling (APS) in FPAI, there are several research challenges that need to be resolved.

Firstly, how the APS problem is reshaped the PI-enabled manufacturing environment? How to resolve the complex and stochastic nature of production and operation management by capitalizing on the revolutionary power of real-time information and data in the PI-enabled FPAI?

Secondly, how to develop a general framework and solution for manufacturing optimization problems considering their new features in the PI-enabled hyperconnected FPAI? How to discretize the traditional monolithic APS decision into a series of real-time decisions, and how to establish their connections and dependencies using real-time visibility and traceability?

Thirdly, how to design a real-time job allocation and execution mechanism considering the actual shop floor situation such as the availability of men, machines, materials to organize production activities in a smooth and resilient manner in FPAI?

This paper proposes a five-phase framework of the Graduation Intelligent Manufacturing System (GiMS) for achieving Real-Time Advanced Planning and Scheduling (RT-APS) in PI-enabled hyperconnected FPAI. GiMS divides the space and time scopes of a factory into finite areas and intervals to localize disturbances and approximate uncertainties so that the original complex optimization problem is discretized to a series of subproblems with different spatiotemporal characteristics. Corresponding synchronization mechanisms of GiMS are designed to generate a global solution and support real-time decision making at both managerial and operational level. Finally, a numerical study is conducted to evaluate the performance of the proposed method. And several managerial insights are offered based on the results.

The rest of this article is organized as follows. Section 2 reviews relevant literature. The GiMS-enabled FPAI are presented in section 3. Section 4 explains the detailed synchronization mechanisms of GiMS. The numerical study is conducted in section 5. Finally, section 6 summarizes the paper and gives future perspectives.

2 Literature Review

2.1 IIoT-enabled Smart Manufacturing

The concept of IIoT is closely related to PI-enabled manufacturing (Zhong et al., 2017a). As one of the cutting-edge technologies in industry 4.0, IIoT promises to construct seamless connectivity between production elements and improve data and information visibility of the shop floor (Guo et al., 2020c). The pioneering researches on IIoT application in manufacturing include identification technologies such as Auto-ID, RFID. Udoka (1991) presented an overview of automated data capture technologies and claimed that these technologies are critical to the success of automated manufacturing systems. Huang et al. (2008) proposed a RFID-enabled wireless manufacturing framework to improve operational efficiency in adaptive assembly planning and control. Zhong et al. (2013) designed a real-time RFID-enabled MES to support real-time production decisions. Lin et al. (2018b) applied iBeacon technologies that provided real-time visibility to facilitate decision-making for supervisors and daily operations for workers. More recently, the potential of industrial wearables is also widely investigated (Kong et al., 2019; Li et al., 2019). Thanks to the extensive applications of IIoT technologies, vast amounts of production data are accessible. Kusiak (2017) and Kuo and Kusiak (2019) revealed the importance of big data in smart manufacturing and identified five gaps to filled for realizing the next industrial revolution.

Indeed, manufacturing is getting smarter with the deployment of IIoT devices, and massive production data are real-timely available in such an environment. However, IIoT is not readily served as an effective mechanism for the conversion from data to valuable information and knowledge. Besides, how IIoT technologies reshape the APS problems and how real-time data can facilitate APS decision considering the new features of these problems in a PI-enabled manufacturing environment need further researches.

2.2 Hierarchical/Multi-Period Planning and Scheduling

It is acknowledged that the APS problems are complex and stochastic (Efthymiou et al., 2016; Keller & Bayraksan, 2009). Researchers realize that the breakthrough to next-generation manufacturing is impossible without overcoming the bottleneck of complexity and uncertainty. HPPS and MPRH are two typical approaches to manage complexity and uncertainty.

The core idea of HPPS is to decompose planning and scheduling problem into subproblems with limited complexity and uncertainty (Bitran et al., 1982; Dempster et al., 1981). Omar and Teo (2007) developed a three-level hierarchical approach in a batch process environment, and the proposed method is tested and validated using industrial data. More recently, O'Reilly et al. (2015) presented an overall decision-making framework for small- and medium-sized food manufacturers with the applications of HPPS. Menezes et al. (2016) studied planning and scheduling problem in bulk cargo terminals and proposed a hierarchical approach with a mathematical model for integration. MPRH discretizes the planning and scheduling horizon into multiple time periods which are short enough with manageable uncertainty (Sridharan et al., 1987). Balakrishnan and Cheng (2007) gave a comprehensive review of research to address the reconfiguration and uncertainty issues in cellular manufacturing under conditions of multi-period planning horizons. Torkaman et al. (2017) presented MIP-based heuristic models with rolling horizons to solve a multi-stage multi-product multi-period capacitated flow shop planning problem with lot sizing.

HPPS and MPRH were proven to be effective in traditional manufacturing settings. Nevertheless, the two methods are hampered by the amplified complexity and uncertainty in the modern manufacturing environment because both required but suffered from the lack of updating mechanisms to integrate subproblems (Omar & Teo, 2007).

2.3 Manufacturing Synchronization

The emergence of manufacturing synchronization (MfgSync) provides a new perspective of production and operations management in the era of industry 4.0. The idea of MfgSync is mostly related to just-in-time (JIT) philosophy, which was firstly proposed by Toyota (Sugimori et al., 1977). JIT advocates that "all processes produce the necessary parts at the necessary time and have on hand only the minimum stock necessary to hold the processes together." JIT aims to reduce the production lead time and inventory level. In contrast, MfgSync focuses on synchronized order-job-operation management to achieve an overall-well performance regarding cost-efficiency, simultaneity, and punctuality (Guo et al., 2020a).

Relevant research on MfgSync is relatively recent. Riezebos (2011) examined the effectiveness of some new heuristics that are based on insights from assembly system design and workload control, and compare their performance with an optimal solution approach. Chen et al. (2019b) studied MfgSync of scheduling dynamic arrival orders in a hybrid flow shop. Luo et al. (2019a) investigated synchronized scheduling problem of make to order plant and cross-docking warehouse and provided decision-maker with managerial insights to configure the production resource and warehousing resource in different scenarios. In addition, production-logistics, production-shipment synchronization also attracted widespread research attention (Chen et al., 2019a; Luo et al., 2017; Qu et al., 2016).

The concept of MfgSync inspires this study to incorporate real-time synchronization mechanisms into the framework of GiMS to facilitate decision-making in planning, scheduling, execution, and control for PI-enabled hyperconnected FPAI.

3 Graduation Intelligent Manufacturing System for Physical Internet-enabled Hyperconnected Fixed Position Assembly Islands

In this section, the five-phase framework of GiMS for PI-enabled hyperconnected fixed-position assembly islands is developed. The configuration and layout of FPAI are introduced in section 3.1. Section 3.2 illustrates the graduation manufacturing systems for FPAI. Lastly, the five-phase framework to implement GiMS in FPAI is given in section 3.3.

3.1 Typical Layout and Configuration of FPAI

FPAI is a typical manufacturing mode for producing bulky or fragile items. As shown in Figure 1, there are two main areas in FPAI. One area (section 1 in the figure) contains the main manufacturing resources, including operators, equipment, and materials. The other area (section 2 in the figure) illustrates the whole assembly process at a single island. Due to the space limitation, each assembly island is only able to keep the work-in-process, a toolbox, a buffer for one part and consumable materials needed for the assembly task, and some space for the operator. The FPAI requires frequent and accurate movement of manufacturing resources, and the assembly task can be started only when all the required materials, tools and operators are ready.

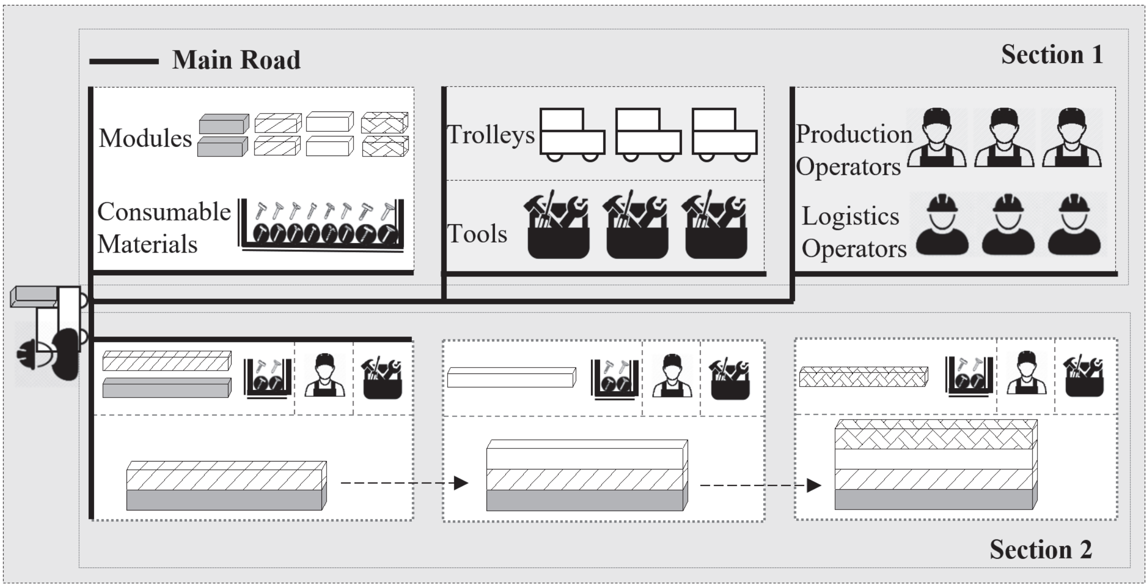

Figure 1: The Layout and Configuration of Fixed-Position Assembly Islands

3.2 Graduation Manufacturing System for FPAI

Graduation Manufacturing System is a novel manufacturing mode that is inspired by the graduation ceremony. Its basic form and principles can be found in previous research (Guo et al., 2020; Lin, et al., 2018). The GMS mode is applied in FPAI.

By analogy to three kinds of tickets used in the graduation ceremony, three kinds of tickets including job ticket (JT), setup ticket (ST), operation ticket (OT) and twined logistics ticket (LT) correspond to admission tickets, program tickets and name tickets are designed in GMS. Figure 2 illustrates the procedure. The workshop production activities are organized and managed through JTs, STs, OTs and LTs with simplicity and resilience. JTs are generated based on real-time customer demand and production constraints to achieve dynamic workload control.

Flexible control of setup can be achieved using STs to avoid unnecessary waiting time and unreasonable setup, and the setup operation can be informed in advance and performed at the right time. OTs and twined LTs ensure the synchronization and coordination of production and logistics processes for JIT delivery.

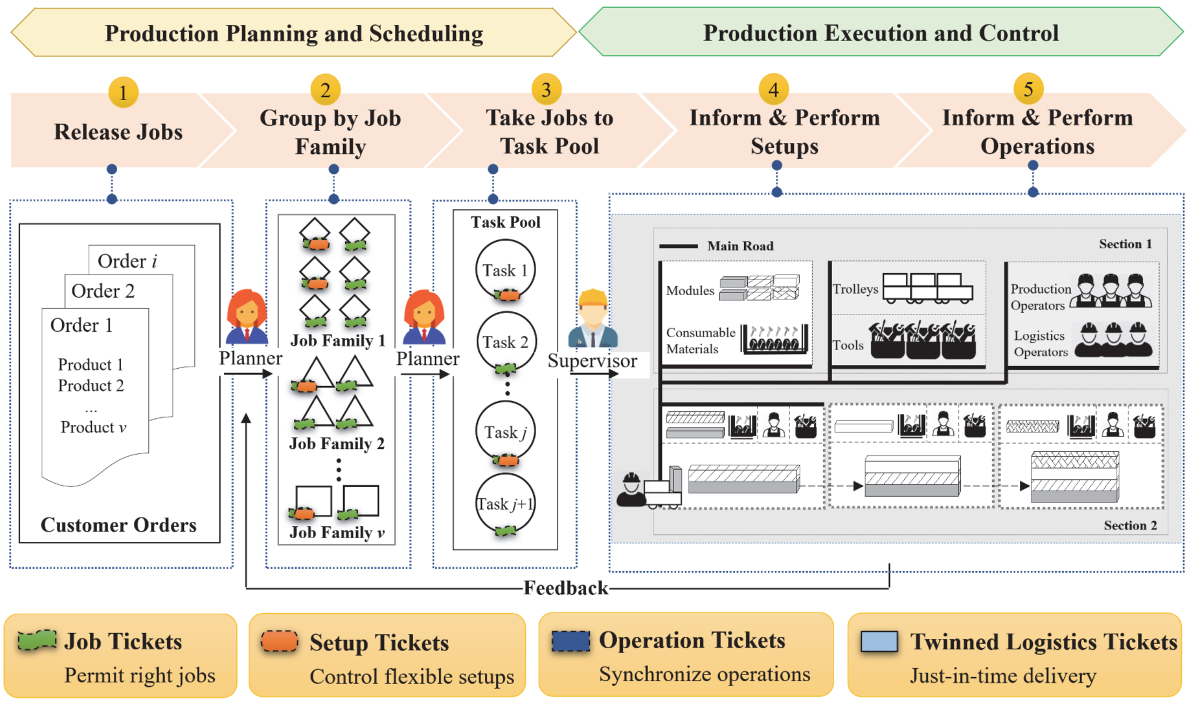

Figure 2: GMS for Fixed-Position Assembly Islands

3.3 The Five-Phase Framework of GiMS for FPAI

Unlike the simple and visible environment, repetitive operation in the graduation ceremony, the actual shop floors are far more complex and dynamic, and the production processes are sophisticated. Therefore, to fully tap the potential of GMS, the real-time information visibility and traceability of the shop floor, real-time coordination and communication among different parties, and real-time synchronization mechanisms for decision-making are indispensable. To overcome these challenges, as shown in Figure 3, this section presents the GiMS with five key phases, namely, Finite meshing, Smart digitization, Out-of-Order ticketing, Visibility and traceability analytics, and Synchronization, for achieving real-time planning and scheduling in PI-enabled FPAI.

The finite meshing phase is to divide the organization and decision horizon of the FPAI workshop into several graduation ceremony stages (GCS, a number of assembly islands in a short time period). Each GCS is composed of several assembly islands. The overall planning horizon is discretized into shorter scheduling periods, which is several hours. This phase minimizes the complexity and localizes uncertainties through spatiotemporal discretization. Operation elements (men, machines, materials) are defined for all "GCS" as physical twins.

The second phase digitizes the operation elements at all GCS for generating digital twins with the PI technologies. With the deployment of mobile crowdsensing and IIoT devices, all physical entities are digitized to provide the FPAI with greater interconnectedness of resources, better circulation of production information flow, and data flow as a solid foundation for a higher level of synchronization. The PI-FPAI is characterized by hyperconnectivity between physical entities, high-quality real-time data, and information acquisition.

The Out-of-Order (OoO) ticketing phase implements the processing logic of operation elements. The OoO in factories organizes the onsite production execution in an order governed by the availability of materials, machines, and men. Operators look ahead in a window of jobs through smart devices and find those that are ready to be processed. The key features of OoO are the high degree of autonomy, flexibility, and resilience at the operational level. The adverse effects of uncertainties can be minimized under OoO ticketing, which will be further discussed in section 4.

The cyber-physical visibility and traceability (CPVT) analytics is utilized to identify and establish the dependencies and connectivity of GCS and operation elements and to mitigate the spatiotemporal uncertainties. The dependency and connectivity usually refer to the logical relationship between GCS, such as how the state of ticket pools update over time and how the tickets flow between elements. These real-time data and information are vital for supporting synchronized decision-making.

The last phase designs the synchronization mechanisms under GiMS to facilitate upper-level planning and scheduling (synchronized ticket allocation) and lower-level onsite execution and control (real-time ticket sequencing). Detailed models and algorithms will be presented in Section 4. The bi-level synchronization mechanism promises both optimized decisions at the managerial level and resilience execution, flexible control at the operational level.

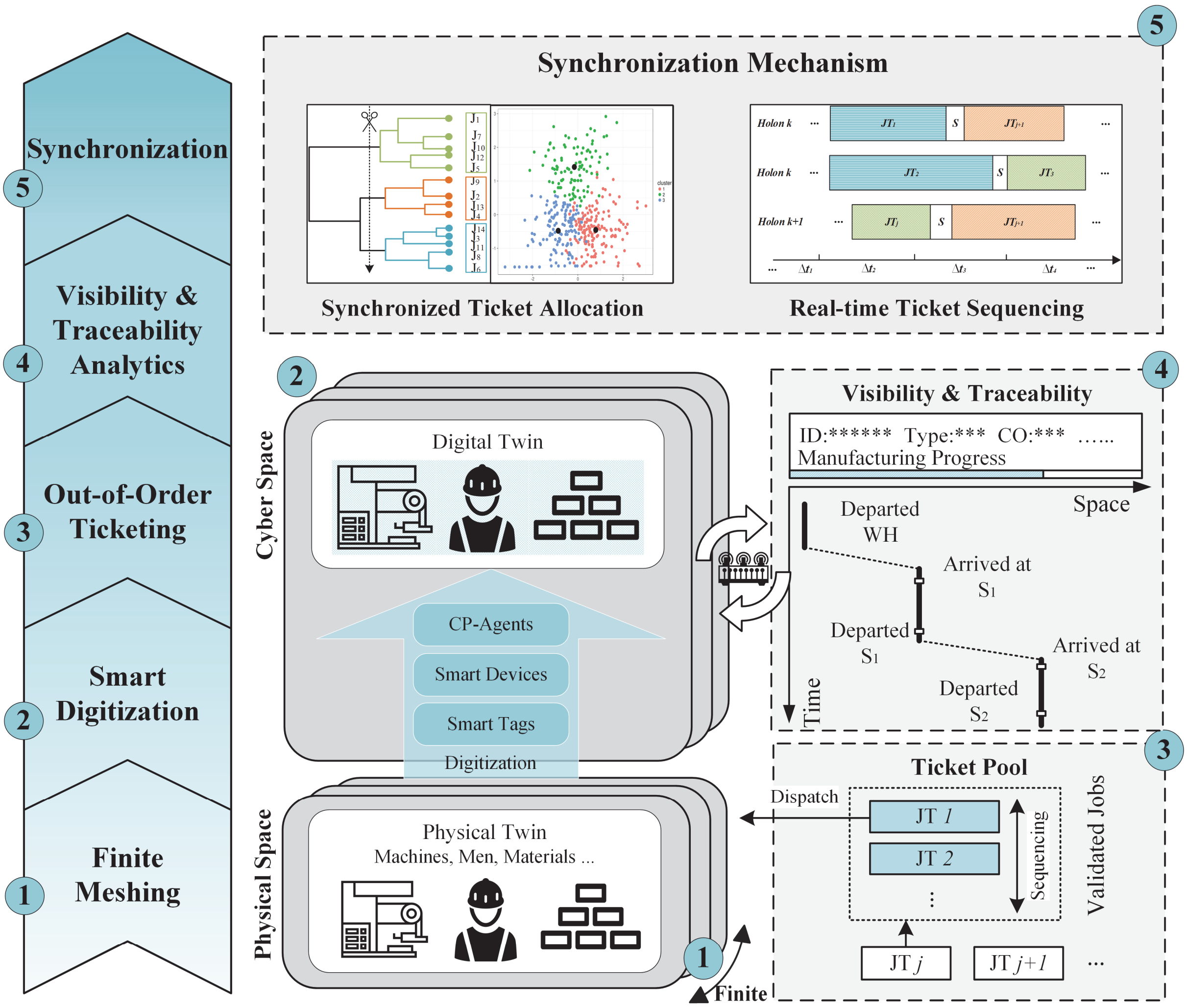

Figure 3: Five-Phase Framework of GiMS

4 Synchronization Mechanisms of GiMS

The synchronization mechanisms and algorithms are the core of GiMS. The original intention of GiMS is to cope with shifting events by sticking to a fundamental principle. Instead of generating a rigid production plan and schedule, similar jobs are clustered into job families and assigned to each GCS in GiMS. It is precisely because the jobs in the same cluster are similar, an exact processing sequence within the cluster is less significant. In section 4.1, the synchronized ticket allocation mechanism is designed for planning and scheduling at the managerial decision level. In section 4.2, the real-time ticket sequencing is developed for onsite execution and control at the operational decision level.

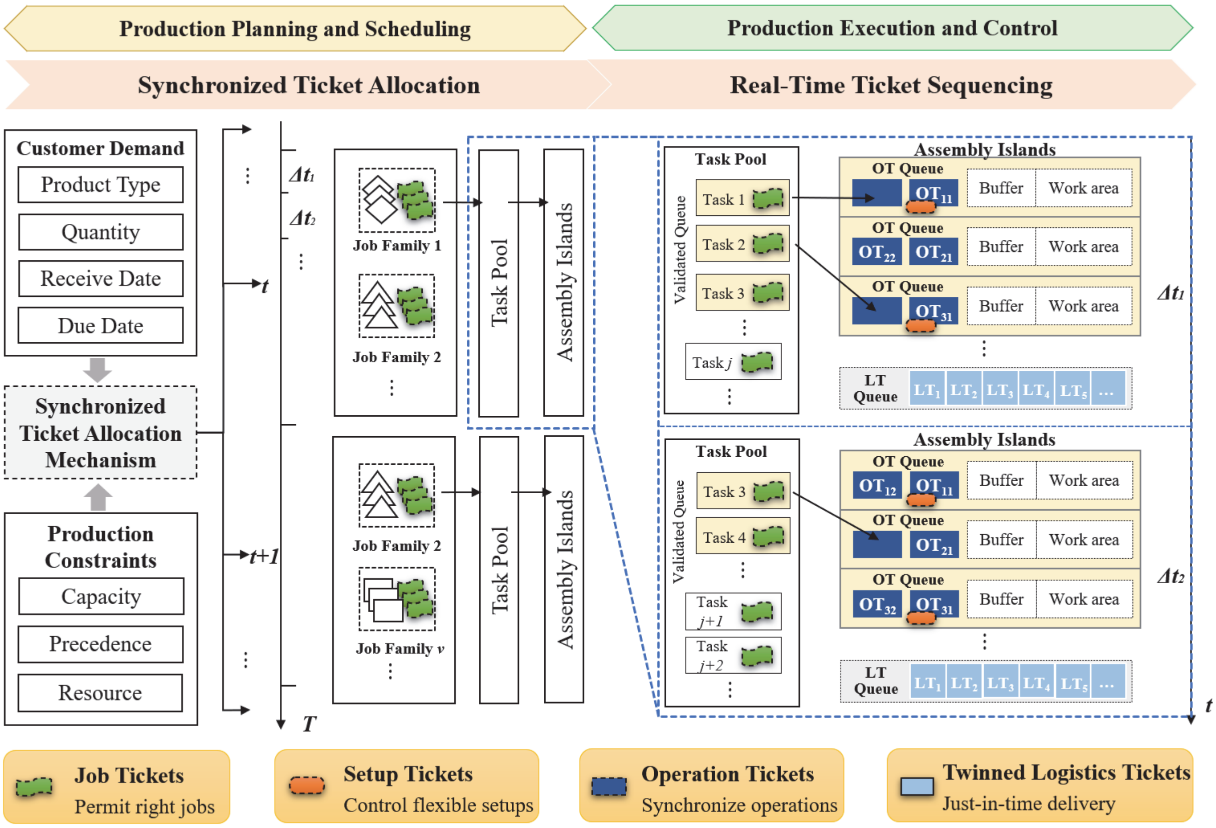

Figure 4: Bi-level Synchronization Mechanisms under GiMS

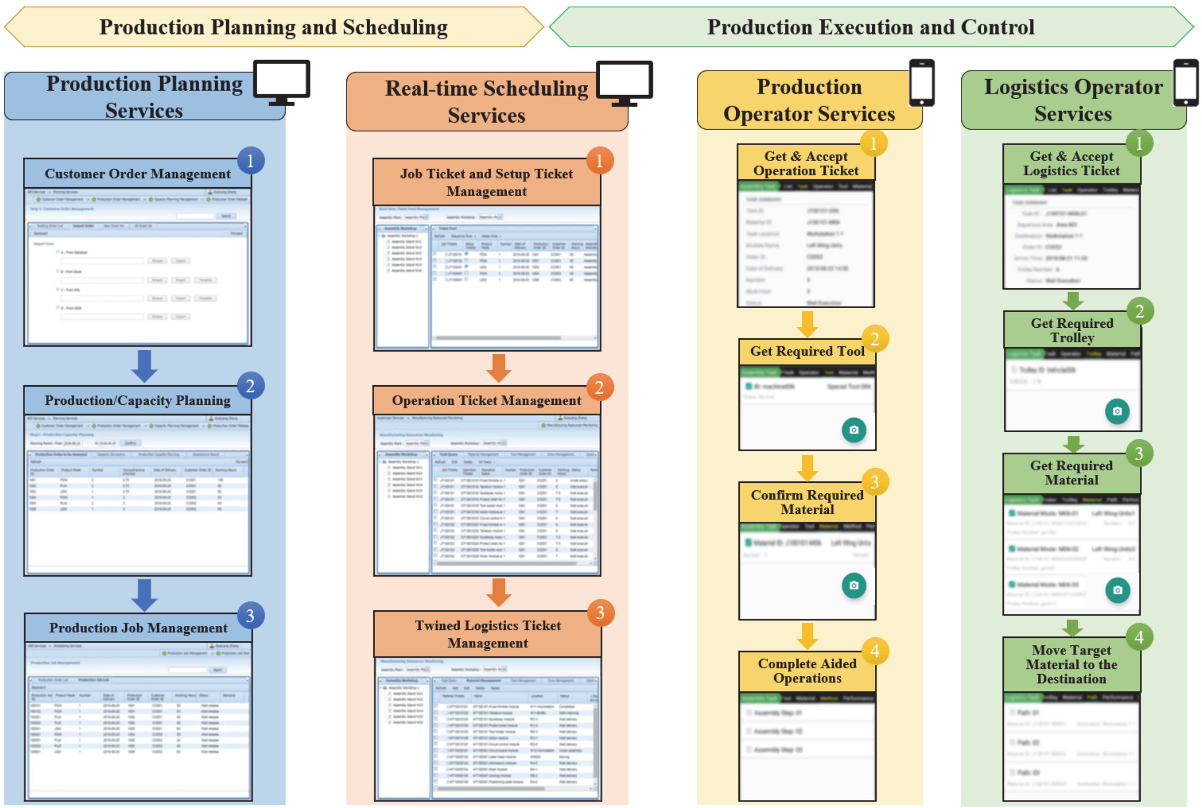

Figure 5: DApp and MApp of GiMS

4.1 Synchronized Ticket Allocation under GiMS

The left half of Figure 4 depicts the production planning and scheduling phase under GiMS. The overall planning horizon T is discretized into multiple shorter scheduling periods t to reduce complexity, localize, and approximate the uncertainties from customers, suppliers, and the market in the time dimension. Based on the real-time traceability and visibility of customer demand (e.g., product type, quantity, receive date and due date) and production constraints (e.g., capacity, resource, and precedence constraints) in period t, the synchronized ticket allocation mechanism aims to generate schedule for period $t + 1$ on an aggregate basis for families of jobs (identical or similar products) and allocate job tickets. The similarity among jobs is usually measured from the aspects of setup, material requirement, operator skill requirement, due date, correlative orders and so on (Lin et al., 2018b). Methods such as clustering analysis, mathematical programming, auction-based approaches are commonly applied at this stage. Since the scheduling period t is short relative to the planning horizon T and the exact processing sequence is not considered at this moment, the less computational effort is required. Thus, the ticket allocation mechanism can be run in near real-time to provide shop floor supervisors and managers with advanced planning and scheduling services for coping with frequent changes from customers, suppliers, and the market promptly, reliably, and positively. Besides, this mechanism allows great flexibility for job execution and progress control at the operational level.

In the FPAI case, the jobs within the same customer order and the jobs that require less setup time for changeover tend to be clustered. The hierarchical clustering is adopted, the distances of jobs are given as:

$$d(i, j) = w_1 \cdot d_1 + w_2 \cdot d_2 \tag{1}$$

Where d_1 takes value 0 if the two jobs are in the same order, 1 otherwise. d_2 is positively correlated with the setup time for changeover between job i, j. w_1 and w_2 are the weighting factors of d_1 and d_2 respectively.

And then, linkages are generated between pairs of jobs that are close together to form binary job clusters. These newly formed binary job clusters are further linked to each other to create bigger clusters until all the jobs are linked together to form a hierarchical tree. And the similarity of clusters a, b is given as

$$d(a,b) = \sqrt{\frac{2n_a n_b}{n_a + n_b}} \left\| \overline{a} - \overline{b} \right\|_2 \tag{2}$$

Where the $\overline{a}$ and $\overline{b}$ denote the centroids of clusters a and b, n_a and n_b the number of jobs in clusters a and b.

The synchronized ticket allocation mechanism is integrated in GiMS as the production planning services and real-time scheduling services that can be accessed through Desktop Application (DApp) to support managerial decision-making. As shown in the left half of Figure 5, The production planning service is used by planners to make short-term production plans. Three sub services, namely customer orders management, production/capacity planning, and production job management, are included. The customer orders are imported and updated through customer order management explorer, and the sequence of orders is determined by priorities (due date, the importance of the customer, etc.). The production/capacity planning service calculates which customer orders can be completed based on the available capacity within the given period. The result is converted into the production schedules and similar jobs are clustered as families that will be released into real-time task pools one by one in production job management service. The workshop production activities are organized and managed through JTs, STs, OTs, and LTs in real-time scheduling services for supervisors. Based on the real-timely monitored workload and capacity of the assembly islands, job families are released automatically and dynamically to balance the whole workshop. Once a job family is released, the JTs and STs are generated and managed in JTs and STs management service. Flexible adjustments for coping with disturbances can be made automatically or by dragging and dropping. Correspond logistics tasks, production tasks and LTs, OTs will be generated and managed in the LTs and OTs management service respectively. The systematic implementation and integration of planning and scheduling services in DApp of GiMS ensure simple but effective managerial production decision-making.

4.2 Real-Time Ticket Sequencing under GiMS

The right half of Figure 4 presents the production execution and control phase under GiMS, as the jobs allocated to a single scheduling period are similar, rigid and exact sequencing of these jobs is less significant. Thus, OoO execution of tickets is adopted to eliminate uncertainties and control the onsite production process with robustness and resilience. At the beginning of period t, correspond JTs are released to the shop floor task pool, the OTs and twined LTs for this job are activated. A JT enters the validated queue once all required resources (e.g., operator, material, machine, or tool) are available. That is, validated jobs are ready for processing. Real-time sequencing mechanism is applied to achieve synchronization at the operational level, the priority of validated tickets is computed based on Horizontal Synchronization (HSync), Vertical Synchronization (VSync) (Lin et al., 2018b), is calculated as follows:

$$P_j = w_3 * H_{sync} + w_4 * V_{sync} \tag{3}$$

Where H_{sync} represents the production progress of the order that contains job j. V_{sync} reflects the matching degree of the job j and the available assembly island k (whether the setup is required). w_3 and w_4 are the weighting factors.

Let o denote the order that contains job j, UJ_o, RJ_o, and FJ_o denote the total processing time of currently unreleased jobs, released jobs, and finished jobs of order o respectively, ε is an arbitrary small real number in case RJ_o and FJ_o equal to 0. Where f_k denotes the setup condition of assembly island k left by the previous job. H_{sync} and V_{sync} can be calculated as follows.

$$H_{sync} = UJ_o^{\frac{1}{RJ_o+FJ_o+\varepsilon}} \tag{4}$$

$$V_{sync} = s_{f_j,f_k} \tag{5}$$

When there is a vacancy in the assembly island ticket queue, the sequencing is triggered and the priority is calculated based on real-time data, the job ticket with the highest priority will be dispatched to fill the vacancy, and ST will be issued accordingly if it is required. In general, the length of the island ticket queue is set as Δt, and a ticket is "frozen" once entering the assembly island ticket queue, which means it will not be re-dispatched to avoid confusion in the shop floor. OoO guarantees smooth execution of jobs and flexible control of production progress to enhance the overall scheduling resilience in the highly dynamic and stochastic shop floor.

The real-time ticket sequencing mechanism is integrated into GiMS as the production/logistics operator services that can be accessed through Mobile Application (MApp) to facilitate onsite production execution and control. As shown in the right half of Figure 5, with the support of the real-time task pool management and production operator service, the production operator can explore the detailed OTs of the assigned JTs via the MApp on the smartphone. Once a vacancy is detected in the assembly island buffer, the validated job ticket with the highest priority will be assigned. Only the right materials are checked and confirmed, the production operator can start the specific operations with the required tools. Moreover, when suffering uncertain events, the production operator could identify and report them timely to the supervisor for further decision-making, which can minimize the impact of uncertainties. In the logistics operator service of MApp, the real-time identification and location information are available, the logistics operators can get logistics task in MApp and easily find the target trolleys and materials and move them to the designated areas. One logistics task can be submitted by the logistics operator only when the target materials are detected and confirmed at the right places at the right time through the system..

The combination of ticket allocation mechanism and real-time ticket sequencing serves as the theoretical and logical basis of GiMS, cloud services-based system implementation (DApp and MApp) guarantees the usability, adaptability, and stability of GiMS in the real-life industry with simple and effective production planning and scheduling as well as smooth and resilient onsite production execution and control. Table 1 presents the pseudocode of proposed synchronization mechanisms.

Table 1: Pseudocode of the synchronization mechanisms

Pseudocode of the synchronization mechanisms

```
Run at the beginning of each t
Inputs: the number of GCS, the number of islands per GCS, scheduling period t,
customer orders, availability of production resources
Outputs: the jobs allocated to this period, the processing sequence of allocated jobs
Update the system status (order pool, job pool, finished jobs, availability of
resources)
Estimate the production capacity of each GCS
Calculate the similarities among all pending jobs
Cluster the jobs by their similarities using Hierarchical Clustering
For k ← 1 to the number of GCS
    Allocate clustered jobs to GCS k based on its capacity
    Generate corresponding Job Tickets for GCS k
End For
Update unreleased jobs, released jobs to task pools
While the task pools are non-empty
    Check the first available GCS k′
    Check the first available island of GCS k′
    For i ← 1 to the number of Job Tickets for GCS k′
        Calculate the Hsync index and Vsync index
        Update the priority of job ticket i
    End For
    Dispatch the job ticket with the highest priority to the first available island of
    GCS k′
    Update task pools, finished jobs
    If current time >= next t
        Break
    End If
End While
```

5 Numerical Study

This section carries out a numerical study to verify the effectiveness of the proposed GiMS. Three performance measures are used in the numerical study: 1) Makespan (MS); 2) Total Setup Time (TST); 3) Total Tardiness (TTD). The experimental data are randomly generated from Table 2. The assumptions are listed as follows:

- Customer orders arrive dynamically;
- Setup is required for changeover between different product families;
- Assembly islands are homogeneous;
- Each island can only process one job at a time;
- Preemption of jobs is not allowed;
- The transportation time for jobs is negligible.

Table 2: Experimental data

Data	Value
Total number of islands	12
Number of islands per GC stage	2, 3, 4
Total number of customer orders	15, 30, 45
Number of jobs per order	20
Number of product families	10
Number of jobs left from last shift	100
Processing time (min)	U [40, 60]
Setup time (min)	U [5, 25]
Orders inter-arrival time (min)	Pois(60)
Due dates of orders	U [3, 5]×8×60

5.1 Parameters Setting

The number of islands per GCS, t, and combination of weights are important parameters of the proposed synchronization mechanisms that will be properly set through the following experiments.

The number of islands per GCS is set as 2, 3, and 4, and the t is set as 60, 120, 180 and 240 mins (see Table 3). Figure 6 gives the curves of the three measures. Generally, the tendencies of MS, TST are similar despite the number of islands per GCS. As the t extends, the MS and TST decrease, and the amplitude of variation is relatively flat when t is equal or greater than 120 mins. This is possible because there are more jobs in the pool with the dynamic arrival of orders, the possibility to find similar jobs is higher (less setup time for changeover), and more orders are considered in one period (longer waiting time for each order). It implies that it is preferable to set a larger t when the company has high setup cost. TTD shows fluctuations as t ranges from 60 to 240 mins, and lower values can be obtained when t is set as 120 and 180 mins. The number of islands per GCS has a relatively limited impact on the performance. Generally, more islands per GCS performs better on MS and TST, less islands per GCS performs better on TTD. In a comprehensive perspective, it is preferred to set 3 islands per GCS and $t = 120\ mins$ for the following experiments.

Table 3: The performance of the different number of islands per GCS and t

	t			
	60	**120**	**180**	**240**
2 islands per GCS				
MS	3242	3105	2906	2856
TST	7136	5348	3105	2637
TTD	15	0	259	1
3 islands per GCS				
MS	3270	2980	2919	2897
TST	7199	4023	3367	3070
TTD	0	299	273	383
4 islands per GCS				
MS	3196	3017	2895	2902
TST	6298	4165	3082	2849
TTD	1521	434	335	2056

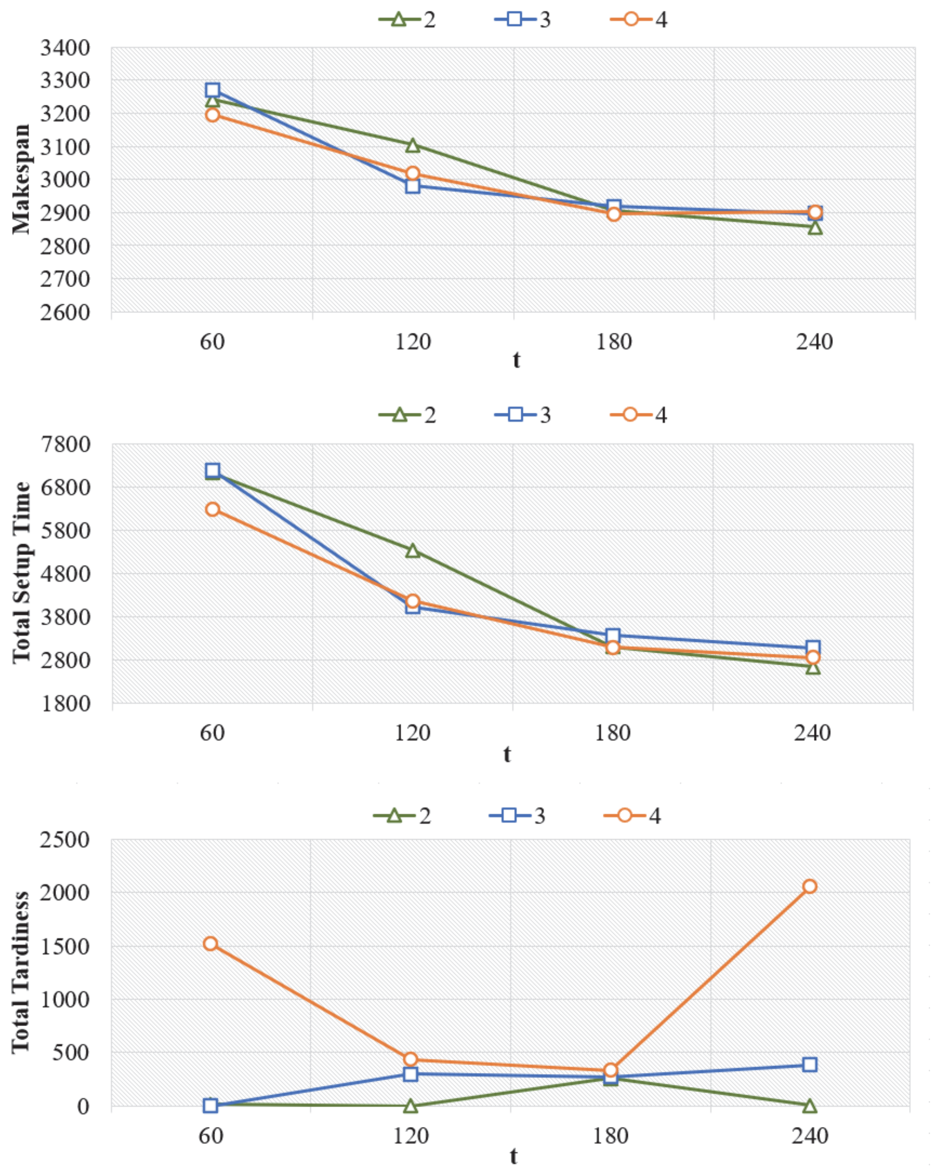

Figure 6: The performance of the different number of islands per GCS and t

There are 4 crucial weights in the proposed solution algorithm, namely (w_1, w_2) in the ticket allocation mechanism and (w_3, w_4) in real-time sequencing. In this experiment, (w_1, w_2) and (w_3, w_4) are set as (0.25, 0.75), (0.5, 0.5), and (0.75, 0.25) respectively, in total 9 combinations of weights are considered as shown in Table 4 and Figure 7. It is found that (w_1, w_2) have a greater impact on the performance than (w_3, w_4), this indicates that the exact processing sequence of jobs within a single period t is less significant because the jobs allocated to one period are similar, and it also means more flexibility for onsite operators to make adjustments to cope with uncertainties to achieve smooth execution and resilient control of production when (w_1, w_2) are properly set.

Table 4: The performance of different combinations of weights

w_1, w_2		w_3, w_4: 0.25, 0.75	0.5, 0.5	0.75, 0.25
0.25, 0.75	MS	2940	2919	2931
	TST	3333	3287	3315
	TTD	169	0	186
0.5, 0.5	MS	2984	2980	2972
	TST	4010	4023	4000
	TTD	299	299	663
0.75, 0.25	MS	3073	3047	3070
	TST	5046	4834	4837
	TTD	0	0	0

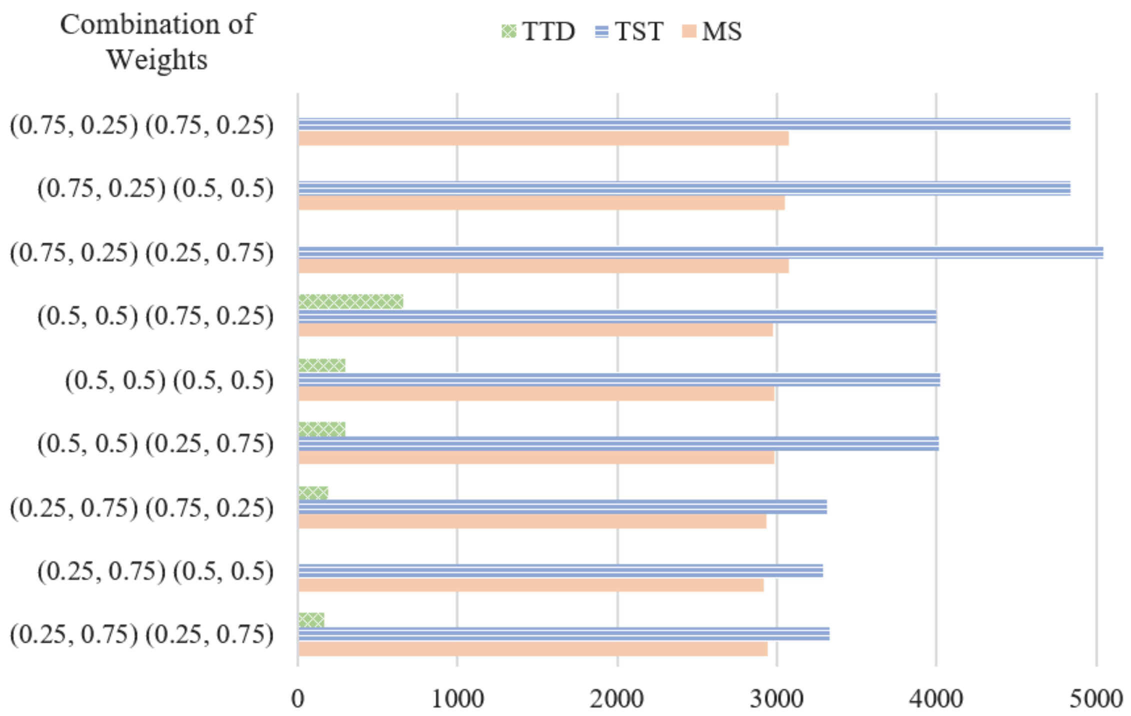

Figure 7. The performance of different combinations of weights

5.2 Performance Evaluation

The experiment below evaluates the performance of the proposed method under various configurations. Three typical dispatching rules are adopted as references.: 1) Earliest Due Date (EDD), which is found to be effective in reducing TTD; 2) Shortest Processing Time (SPT), which is one of most classical rules in literature; 3) First-Come First-Served (FCFS), customer orders are processed one by one under FCFS. One important reason for choosing these rules is that they require less computation efforts. In real-time decision-making, the time-limit must be considered (Ghaleb et al., 2020). The proposed method can generate results in a few seconds (even for large size instances), which means it can react to disturbances promptly.

Table 5 presents the results. It is observed that the proposed GiMS outperforms other dispatching rules in terms of MS, TST, TTD, and backlog jobs. The EDD rule suppose to have better performance on TTD and backlog jobs as the most urgent jobs are processed first under this rule. It might be attributed to the frequent setups that actually prolong the whole production process (the TST under EDD is more than triple that under GiMS, and the MS under EED is about 20% longer than that under GiMS). This experiment indicates that the performance of GiMS is well-balanced and relatively stable in a dynamic environment. Besides, the advantages of GiMS are more obvious in normal and high demand.

Table 5: The performance evaluation of GiMS

	GiMS	EDD	SPT	FCFS
15 Customer Orders (Low demand)				
MS	**1514**	1833	1687	1724
TST	**2151**	6066	4448	4876
TTD	**0**	**0**	81	**0**
Backlog Jobs	**0**	**0**	2	**0**
30 Customer Orders (Normal demand)				
MS	**2919**	3567	3472	3442
TST	**3287**	11215	10088	9692
TTD	**0**	1705	92567	22388
Backlog Jobs	**0**	27	178	84
45 Customer Orders (High demand)				
MS	**4497**	5273	5302	5141
TST	**6444**	15931	16269	14397
TTD	**18709**	133279	539406	148962
Backlog Jobs	**88**	368	439	304

5.3 Managerial Insights

Based on the numerical results, several managerial insights can be concluded for practitioners. Firstly, the real-time manufacturing data and information provide the managers and supervisors with real-time visibility and traceability. The GiMS is proved effective to generate real-time APS decisions using visibility and traceability. Secondly, in comparison with traditional planning and scheduling strategies, GiMS can obtain overall balanced and stable solutions regarding multiple measures in a dynamic environment. The advantages of GiMS are more obvious in normal and high demand. Thirdly, key parameters should be carefully adjusted according to the actual conditions of the factory. The schedule will be too rigid to lose resilience when space and time scope of a GCS is too small; while it is lack responsiveness to frequent disturbances and the similarity of clustered jobs is weakened if the size is too large.

6 Conclusion

In conclusion, this study has investigated the advanced planning and scheduling problem in the PI-enabled fixed-position assembly islands. With the deployment of IIoT devices, the PI-enabled manufacturing environment is characterized by great visibility, traceability, and hyperconnectivity. A five-phase framework of GiMS with synchronization mechanisms is proposed to tackle the complexity and uncertainty of production and operations management in modern manufacturing. By minimizing the complexity and uncertainty in meshing, the original monolithic APS decision can be discretized into a series of real-time decisions. A global solution is obtained through synchronization mechanisms. Finally, a numerical study was carried out to examine the superiority of GiMS. The results showed that GiMS had a well-balanced and stable performance on selected measures in a dynamic environment.

The contributions of this paper are threefold: 1) It proposed a formalized five-phase framework of GiMS, which can leverage the revolutionary power of real-time data to support production and operations management in the PI-enabled manufacturing environment; 2) It designed the synchronization mechanisms of GiMS to facilitate real-time decision-making at both managerial and operational level; 3) It carried out a numerical study to verify the effectiveness of GiMS and offers some managerial implications based on the results.

Two possible research directions deserve further explorations. On the one hand, a more comprehensive case study might be carried out in the future to consider various uncertain events, adopt more measures like schedule stability and robustness. On the other hand, the application of the five-phase framework of GiMS may be extended to other manufacturing layouts such as job shop and flow shop. It might even be applied to solve other combinatorial optimization problems such as vehicle routing encountered in the real-world.

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