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Decentralized Scheduling and Dispatch Control for the Traditional Labor-Intensive Assembly System

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Abstract

The fourth industrial revolution has broadly transformed the manufacturing system. However, this transformation is somewhat lacking in traditional or manual production systems due to the absence of IT infrastructure. Such traditional industries need to have the advantage of real-time control and monitoring. This study has developed economic assembly planning, scheduling, and control for a traditional assembly system. We used the concept of the configurable virtual workstation as the digitalization framework. Then, we employed the decentralized scheduling concept to reduce the computational effort in scheduling the complex product. The implementation result showed that scheduling and planning have transformed the traditional assembly process into intelligent scheduling and control with low digitalization effort.

Keywords

Decentralized, Scheduling, Control, Assembly, Labor-Intensive, Intelligent Manufacturing Systems.

Introduction

The fourth industrial revolution transforms manufacturing systems (Baheti and Gill, 2011). Technology, such as decentralized computing, automation, data analytics, and the Internet of Things (IoT), has created smart factories that optimize production in real time and respond quickly to changes without human intervention. Consequently, it has also enabled advanced analytics to monitor, control, and optimize production in real time, improving overall manufacturing performance (Lee et al., 2015).

One type of production system is labor-intensive, which relies heavily on human labor instead of robotics in production. The labor-intensive production system is cost-effective in countries or regions where labor is relatively cheap and abundant. This system also allows more flexibility and adaptability. However, IT infrastructure is not usually developed, which means that labor-intensive production systems may not be as efficient or productive as automated production systems that involve more technology and automation (Raharno and Cooper, 2020).

Effective production planning, scheduling, and control enable manufacturers to respond quickly to changes in demand that are highly occurring in such systems (Pinedo, 2005). It directs manufacturers to optimize resources, reduce costs, maintain quality, and improve delivery times. However, accurate planning, scheduling, and control are challenging in the labor-intensive manufacturing system as the information systems are not established. Another challenge comes from the scheduling complexity of labor-intensive systems, where a large number of variables must be taken into account, such as the skill level of the workforce, the availability of workers, and the presence of overtime and shift work.

Despite the many traditional labor-intensive manufacturing systems in use today, there are relatively limited studies in the literature on production planning and scheduling (Hu et al., 2011). This lack of research on labor-intensive systems can be attributed to the perception that they are less advanced than the system with automation. However, as the number of labor-intensive systems plays an essential role in the manufacturing industry, more research must be

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dedicated to transforming them into intelligent labor-intensive systems that can improve their efficiency and effectiveness (Hedman and Almström, 2017).

This study focused on production planning, scheduling, and control in labor-intensive assembly systems. We aimed to develop a model that can effectively consider the various factors that impact scheduling in these types of systems, such as the workstation availability, worker availability, the complexity of the assembly process, and the need to respond to changes in schedule. We also considered the impact of overtime and shift work on schedule. We aimed to provide an economical approach to production planning and scheduling by addressing the unique scheduling challenges in labor-intensive assembly systems.

The product presented in this study was complex, with a multi-level structure that required careful consideration of the components and sub-assemblies that comprised the final product. The multi-level structure of the product meant that production planning and scheduling must consider the different levels of the assembly process and how they interact. The planning and scheduling include ensuring that all necessary components and sub-assemblies were vailable and that the assembly process was completed as efficiently and cost-effectively as possible.

The structure of this paper is as follows. We first present a thorough literature review on the current state of the art in labor-intensive assembly systems, focusing on production planning and scheduling. Then, we discuss the challenges and limitations of traditional scheduling methods and the need for advanced, decentralized approaches. We introduce our proposed decentralized production planning and scheduling model in the Material and Method section. We also provide an overview of the configurable virtual workstation, enabling decentralized scheduling in labor-intensive production systems, followed by a case study's results, demonstrating our proposed model's effectiveness in a real-world assembly system. We also highlight the limitations of our proposed model and suggest areas for future research. Finally, we present our conclusion and summarize the key findings of our study in the last section.

Literature review

Many assembly lines are also labor-intensive, making it difficult and expensive to implement automated control systems. Assembly lines involve many variables that must be considered, such as multi-layered product and process structure, the tools availability, inventories, the workforce's skill level, and the workers' availability (Guide et al., 1997). Also, many product types are highly customized, and developing a general control system is challenging. The lack of control led to errors and inconsistencies in the assembly process, resulting in poor sub-assemblies and increased production costs.

Studies on digitalization to form Cyber-Physical Systems (CPS) in labor-intensive production have recently gained attention (Guiza et al., 2021). CPS technology in manual production systems has the potential to transform the assembly systems' operation by coordinating tasks, real-time reporting and control, reducing costs, and increasing the flexibility of production. However, the current CPS systems are expensive and require a significant investment in information technology infrastructure (Tarallo et al., 2018); which makes CPS accessible only to capital-intensive industries but not to most assembly systems which are usually not capital-intensive.

Part 1 Production Scheduling and Dispatching Control on the Labor-Intensive System

Although the literature is rich with production scheduling methods, only a fraction of the study is dedicated to the manual production system, much less to the traditional assembly system (ElMaraghy and ElMaraghy, 2016; Kärcher et al., 2018). The challenges come from the complex and dynamic nature of the assembly process and the absence of IT infrastructure. A study of real-time control in a manual assembly workshop was implemented in a learning factory [X] (Sudhoff et al., 2020). Six workstations are equipped with a scanner and microcontroller to identify the workpiece through a QR code. This system enables real-time data acquisition, production, and visualizing the factory's KPI achievement.

Many traditional labor-intensive assembly systems still rely on spreadsheet-based methods, which can be inadequate and inefficient (Hedman and Almström, 2017). These manual methods often result in poorly recorded data, leading to nontransparent data, inconsistencies, and errors in the recording. The production planning and scheduling methods are not linked to the monitoring systems. It is difficult to track the production process's performance in real time and make adjustments as needed.

One characteristic of the assembly is the multi-level product structure, which often challenges the configuration of planning and control due to its scheduling complexity. Several studies on automated planning and scheduling have been published in the literature.

A study proposed a concept of an adaptable assembly system that gives autonomy to workstations and robots to configure the assembly work (ElMaraghy and ElMaraghy, 2016). A study proposed an automated scheduling approach to generate a daily assembly schedule in the automotive industry (Lewandowski and Olszewska, 2020). The studies commonly solved the problem using different scheduling algorithms. A study solved a multi-level product structure scheduling with simulated annealing and heuristics algorithms (Jung-Ug Kim and Yeong-Dae Kim, 1996). Also, some studies were performed from recoverable manufacturing related to the re-assembly of a complex product. Comparison can be made to the job-shop production or assembly solved by integer linear programming and genetic algorithm. Note that such studies were performed with significant effort and investment.

Often, the multistage operation is also applicable in complex assembly lines. It is distinct as it allows different stages of the tasks to be scheduled. Assembly flow shop scheduling is a specific type of assembly scheduling that coordinates multiple stages of the assembly process, such as assembly, testing, and inspection. The product structure and process determine the layout and the number of workstations in the assembly lines. A study proposed an approach to a two-stage assembly scheduling problem, where they proved that it is an NP-hard. Another study solves the three-stage assembly flow shop problem with simulated annealing.

Dispatching rules for scheduling in the job shop system is an NP combinatorial optimization problem. Some research is dedicated to a manual production system. Dispatching rules were developed for roofing manufacturing, where they proposed a combinatorial algorithm for dispatching jobs (Ren et al., 2022). A study claimed that flexible job shop scheduling is an NP-hard problem, and therefore they utilize genetic algorithms in developing a production schedule (Li and Gao, 2016). However, most manual production studies have not integrated their scheduling result into the real-time dispatch control. We believe the lack of IT infrastructure in the manual production settings also causes this problem.

In this study, we focused on closing the gap in the scheduling and dispatching control problem of the traditional labor-intensive assembly system with minimum investment or systemic change.

Part 2 Digitalization of the Traditional Assembly Systems

The fundamental challenge of the labor-intensive manufacturing system is the absence of IT infrastructure that functions as an interface between the production floor to the data center. Studies and research on adding a digital interface such as RFID, handheld, or sensors are scattered in the industries. Examples include farming, textile, and some production systems (Braun et al., 2018; Charania and Li, 2020; Gökalp et al., 2019; Kim and Moon, 2020; Tarallo et al., 2018). All these studies focus on enabling data acquisition from the shop to the data center.

Materials & Methods

In this study, we used the configurable virtual workstation concept (CVWS) (Fig. 1) designed for the manual and labor-intensive manual to be digitally transformed. The early version was implemented in the manual machining shop (Hartono et al., 2018, Hartono et al., 2020). We focused on the scheduling algorithm for a complex product assembly. In CVWS, all components are modeled in an analogous cyber-physical system, where the components, sub-assembly, tools, workers, workstations, and each product are intelligence capable.

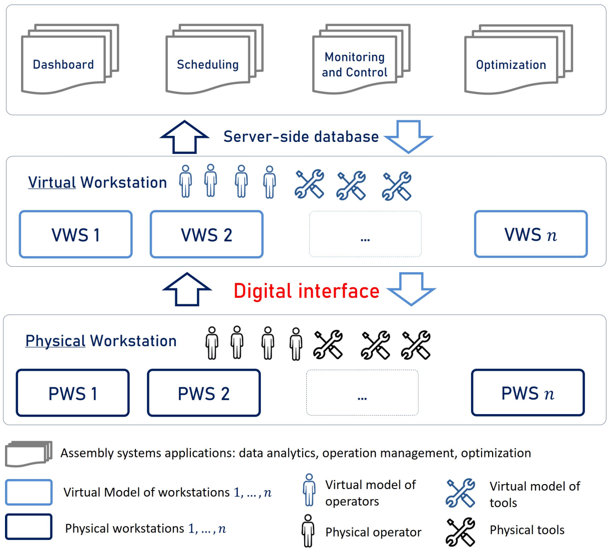

Fig. 1. Configurable Virtual Workstation (CVWS)

This study used a multi-level product structure. The final assembly comprises subassemblies and components, as shown in Fig. 2. Every component and subassembly is pre-processed and assembled in the assembly shop. The scheduling and planning aim to assign subassemblies and assembly operations sequences to minimize tardiness. Then, the result of the scheduling will be used in the real-time control of the assembly system.

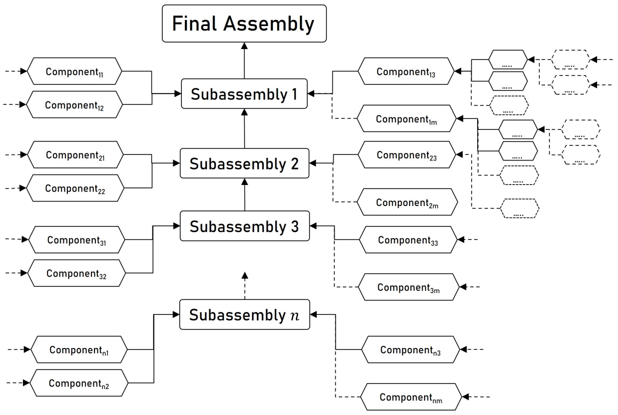

Fig. 2. Complex Product Structure

We defined several terminologies as follows. New jobs are typically defined when customers place their orders. At this level, we call such an order a new project. Each project comprises batches of products with similar technical specifications. Then, the central CVWS system generates the list of components and subassemblies to be assembled based on the bill of material (BoM) of a specific product. The bill of process (BoP) follows the BoM at this stage. For example, a new project consisting of 2 distinct products, A and B. The CVWS will generate product A and B components to be scheduled and assigned to the production department.

The goal of scheduling is to assign three main parts to the schedule: the components and subassemblies, the workstations, and the labor based on the bill of process. Note that in assembly operations, the workstations are flexible and configurable into different operation types. The material planning will be done once the schedule is generated.

Part 1 Backward Scheduling Method

To show the details of the scheduling scenario, we present the following mathematical formulation. However, this formulation is not solved analytically in this study; instead, it serves as a basis for developing the heuristics algorithms in the next section.

The mathematical formulation considers several assumptions. The model assumes that the transportation and setup time are negligible and do not significantly impact the scheduling of the assembly process. Inserted idle time is not allowed, meaning the assembly process must be completed according to the assigned time allocation. Preemption of jobs is also not allowed, meaning that once a job is started, it must be completed without interruption. Another assumption is that all operations are available at time zero, and there is no limit on the buffer size between two workstations, meaning that all resources, including labor and equipment, are available from the start of the assembly process.

First, we define the parameters and variables for our formulation.

i	Subassemblies index $i = 1, 2, .., l$
j	Workstations index $j = 1, 2, ...n$
k	Product index $k = 1, 2, .., m$
t	Time Index
T	Completion time of product k
d_k	Due date of product k
s_j	Set of subassemblies that can be processed at workstation j
x_{ijkt}	Binary decision variable that is equal to one if subassembly i is processed at workstation j at time 0
y_k	Binary decision variable that is equal to one if product k Is completed before or on its due date
z_k	A non-negative variable that represents the tardiness of product k

The first constraint shows that every subassembly can only be processed once in one workstation. The second constraint shows that every workstation can only process one subassembly for a given product. The third constraint ensures that each assembly must be processed according to its BoM.

The fourth constraint specifies that the final assembly completion time must be greater than or equal to the sum of the completion times of its subassemblies. The fifth constraint ensures that the product completion time is less than or equal to its due date. The sixth constraint shows that tardiness is the positive value showing the difference between the completion time and the due date. The seventh constraint ensures that every subassembly is processed before the final assembly. The eighth and ninth constraints show the binary constraints for both decision variables. The last one is the non-negativity constraint for tardiness. The complete formulation is as follows.

$$\min z_k$$

$$st \quad \sum_{j\epsilon J} \sum_{t\in T} x_{ijkt} = 1 \, \forall ijk \tag{1}$$

$$\sum_{i\in s_j} \sum_{t\in T} x_{ijkt} \leq 1 \, \forall jk \tag{2}$$

$$x_{ijkt} \leq \sum_{m\in J} \sum_{t'=0}^{t-p_{ij}} x_{mjkt'} \, \forall ijkt \tag{3}$$

$$\sum_{j\epsilon J}\sum_{t\in T} t.x_{ijkt} \le \sum_{j\epsilon J}\sum_{t\in T} t.x_{sajkt} + M.(1-y_k)\,\forall ik \tag{4}$$

$$\sum_{j\epsilon J}\sum_{t\in T} t.x_{ijkt} \le d_k + M.(1-y_k)\forall k \tag{5}$$

$$z_k \ge \sum_{j\epsilon J}\sum_{t\in T} t.x_{ijkt} - d_k \forall k \tag{6}$$

$$\sum_{j\epsilon J}\sum_{t\in T} t.x_{ijkt} \le \sum_{j\epsilon J}\sum_{t\in T} x_{sajkt}\forall k \tag{7}$$

$$x_{ijkt} \in 0.1 \tag{8}$$

$$y_k \in 0.1 \tag{9}$$

$$z_k \ge 0 \tag{10}$$

The computational complexity of the above formulation depends on the number of products and BoM complexity. With the configuration shown in Figure 3, the number of components to be scheduled increases exponentially as the number of products increases. With each additional product, components' possible combinations and dependencies multiply, resulting in an accelerating growth rate. This exponential increase creates a computational challenge for scheduling algorithms as the complexity rises rapidly with the expanding variety and interconnections within the product portfolio. In this case, the product structure consists of five level, represented by the black and white boxes, and each level are to be assembled with other components.

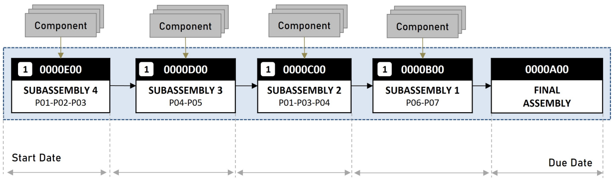

Fig. 3. Backward Scheduling Approach

Figure 4 shows the decision variables explosion example when the number of products increases. To schedule such an assembly process, we use the backward scheduling method. The idea is to use the resource as close to the due date as possible. Thus, the scheduler puts the final assembly completion at the delivery due date.

Part 2 Decentralized Scheduling Method

We used the decentralized concept in generating the schedule, where the production model in the virtual manufacturing system makes the scheduling decision. This method is based on the autonomous distributed manufacturing System (Iwamura and Sugimura, 2010; Yatna et al., 2014). Some studies also acknowledge this method as the auction method (Komine et al., 2020; Yoshihiro Yao et al., 2007). In the decentralized concept, the scheduling was processed by multiple computers instead of one single computer.

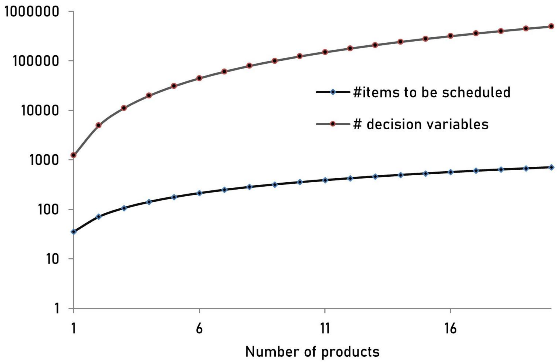

Fig. 4. Decision Variables Increases for Product Structure with Five-Level

Thus far, the challenge of the traditional assembly system is that the elements of each production are disconnected, making a decentralized concept difficult. Therefore, we use the CVWS first to digitalize the manual framework. Once installed, the CVWS adds the monitoring and controlling capability to the production process in labor-intensive scheduling systems. Each workstation now has a "local brain" that decides which operations to perform. At the same time, this workstation can also propose its scheduling availability. The interface between the operator, components, and the central manufacturing execution system is called a smart point, an embedded computer system equipped with IoT, a barcode scanner, a printer, and a database.

The scheduling phase process is described in Fig. 5 and works as follows. The main program generates a production schedule whenever a customer places orders. The scheduling procedures work like an auction method where three actors function as chair, bidders, and biddings. The scheduling coordinator represents the chair, bidders are the workstations, and biddings are the assembly operations. For example, when there are 100 components to be assembled with specific due dates, the coordinator will release 100 biddings to the workstation. Each workstation is the bidder, with the right to bid on their available schedule and capabilities. When all components are scheduled, the coordinator confirms the final master production schedule.

The master production schedule will then generate the material requirement plan for the procurement department. The incoming material will be received at the central warehouse and distributed to each workstation.

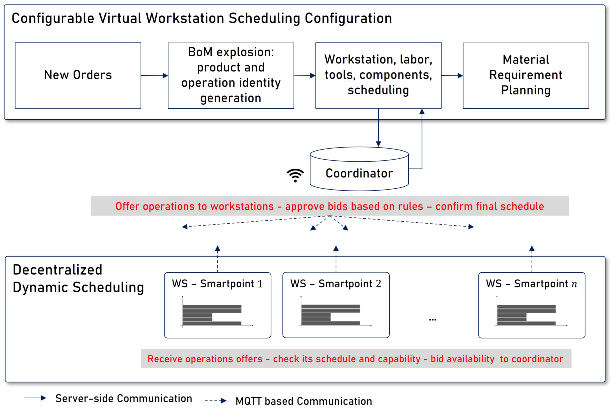

Fig. 5. Decentralized Scheduling within the CVWS Framework

This master production schedule also works as the basis of component dispatching rules and control (Fig. 6). It pushes the production schedule to each workstation through the digital interface, the smart point. As the smart point is intended for the labor-intensive system, it is essential to show only the compliant order to the interface, which means that the component, the worker, and the tools are ready at the workstation according to the schedule. This mechanism guides the worker to work according to the schedule and prevents unnecessary operations.

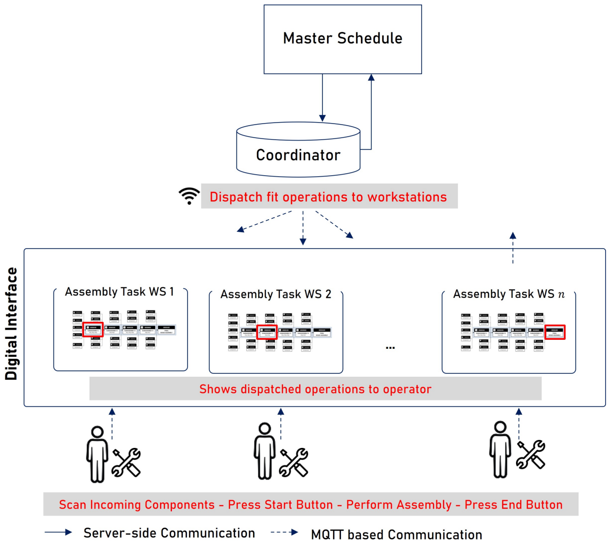

Fig. 6. Job Control and Dispatch

Rescheduling is also challenging in the assembly industry, and it is caused by two main problems. First, each order usually consists of multiple products and a new schedule must be built on top of the existing schedule. The schedule will typically be built behind the first product if the order consists of two or more similar products. At this point, we can no longer assume all machines are available. Furthermore, scheduling the new product will be more challenging when an additional order has different technical requirements and workstation configurations.

Second, since each component depends on its parent, rescheduling will be very difficult to perform in traditional manners. Each component depends on its parent's completion time, so it cannot be processed in a different order than the one specified in the BoM. When a change occurs, the whole schedule must be recalculated from the beginning, and it becomes complicated to change the schedule.

The decentralized scheduling avoids these problems. When rescheduling is needed, the central coordinator collects the operations to be rescheduled and generates biddings for each workstation.

Part 3 Case Study

We implemented the solution to a railway industry's assembling bogie train in Indonesia. Bogie scheduling and dispatch control are critical as they involve coordinating resources and scheduling various stages of the bogie assembly process. In this study case, about two hundred components will be assembled to produce one bogie train, with a structure similar to Fig. 2 and 3. It has five levels represented by the main subassembly; each subassembly in each level has to be assembled with other components.

In the actual implementation, the number of orders can consist of up to dozens of bogie trains. We intend to show the computational efforts by measuring the time duration of scheduling for products with similar and different due dates.

Results

The results of this study demonstrated the effectiveness of decentralized scheduling and dispatching control for labor-intensive assembly systems. Our computational analysis showed that the scheduling process has a linear computational effort when the number of products ranges from one to fifteen. These results indicated that the proposed approach is practical even when the number of products increases.

Figure 7 shows the computational effort required for products or jobs with similar due dates. The results demonstrate that the computational effort is consistent and linear, even for multiple products with similar due dates. This result indicates that the proposed approach effectively manages the scheduling process in a labor-intensive assembly system.

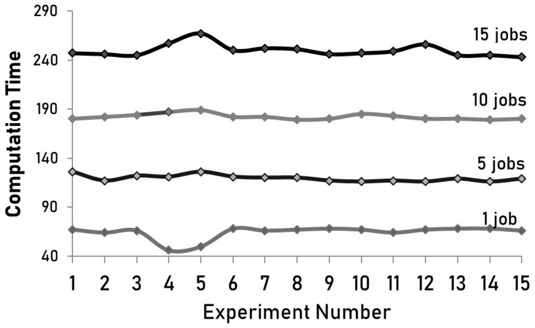

Fig. 7. Computation Time of Scheduling for Jobs with Similar Due Date

Figure 8 shows the computational effort required for products or jobs with different due dates. The comparison of computation time statistics between the two sets reveals valuable insights into the efficiency of our scheduling method. In set 1, representing jobs with similar due dates, the average computation time is 139.95, with a standard deviation of 53.30 and a range of 277. On the other hand, set 2, corresponding to jobs with different due dates, demonstrates an average computation time of 139.09, a slightly lower standard deviation of 50.16, and a comparable range of 221. Note that the mean computation times across both sets exhibit relatively close values, indicating that scheduling for jobs with similar or different due dates does not significantly affect the overall computational effort.

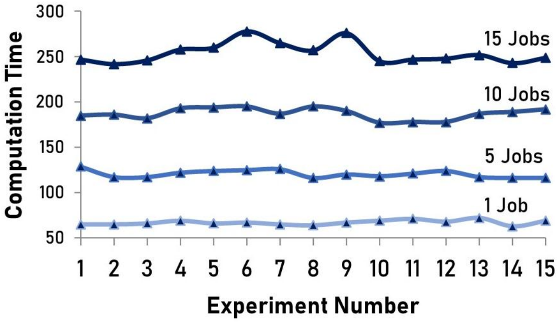

Fig. 8. Computation Time of Scheduling for Jobs with Different Due Dates

Moreover, the two-tailed t-test results show a p-value of 0.9085, signifying that the observed difference in average computation times between set 1 and set 2 is not statistically significant by conventional criteria. This result indicates that the proposed approach can effectively manage multiple products with different due dates in a labor-intensive assembly system.

These results show that the decentralized scheduling approach is effective even when multiple products have different due dates, indicating its feasibility in a real-world production environment.

Discussion

Decentralized scheduling and dispatching control are needed to manage labor-intensive assembly systems. In this study, we proposed a method to develop an environment where scheduling and dispatch control are possible within traditional industries. The scheduling process is a critical aspect of the assembly shop as it affects planning and decision-making in the production process.

The proposed approach is centered around the concept of decentralized scheduling, which allows for the reduction of computational complexity. Decentralized scheduling distributes the responsibility to individual workstations, reducing the computational effort required to schedule complex products. We successfully implemented this approach using the configurable virtual workstation as a digitalization framework.

However, our study also found that the scheduling process is highly dependent on the stability and speed of the network connection between workstations. As demonstrated in Fig. 7 and Fig. 8, network instability resulted in surges in several points, which could impact the scheduling process. Future research should address this issue and develop more stable network connections to improve the scheduling process.

Our study also demonstrated that the proposed approach is applicable and extendable to other manual production systems or similar labor-intensive assembly systems where the primary resource is human operators. The hardware and software involved in the proposed approach are simple and low-budget, making it accessible to various industries.

The proposed approach provides a feasible scheduling and dispatch control solution in labor-intensive assembly systems. Our study contributes to the body of knowledge by demonstrating the effectiveness of the configurable virtual workstation as a digitalization framework and the feasibility of decentralized scheduling. Future research can focus on improving the stability of the network connections and exploring material requirement planning in labor-intensive assembly systems.

Conclusions

In conclusion, our study proposes an economical assembly planning, scheduling, and control framework that leverages the concept of configurable virtual workstations and decentralized scheduling to enhance the performance of traditional assembly systems. Our implementation results demonstrate that this framework can effectively transform the traditional assembly process into an intelligent scheduling and control system with low digitalization effort. This approach could benefit industries lacking IT infrastructure significantly and pave the way for more efficient and flexible production systems. Further research can explore the scalability and applicability of this framework to different industries and contexts.

Acknowledgments

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