SCHEDULING OPTIMIZATION OF MANUFACTURING PROCESS FLOWS USING AGENT-BASED SIMULATION MODELING AND NEURAL NETWORKS

GAKU, R. *

Abstract: *In this study, agent-based simulation modeling is used to build a feasible production system with two parallel manufacturing process flows, each with multiple production processes. The simulation model is constructed by accounting for the occurrence of variations in the system, such as order priorities, processes that vary in time, and the uncertainty of manufacturing resources. The two neural networks are then trained to automatically record training data for each parallel manufacturing process flow. To minimize the average makespan of a variety of orders, neural network trainers are integrated into the simulation model to support decision-making during scheduling optimization. As a result, each order is routed to the production line where the neural network predicts that it will have the lowest makespan.*

Key words: *Operations Management, Production Scheduling, Scheduling Optimization, Simulation, Neural Network*

Authors' data: Prof. Dr. **Gaku**, R[ie]*, University of Momoyama, Faculty of Business Administration, 1-1 Manabino Izumi, Osaka, 594-1198, Japan, r-gaku@andrew.ac.jp

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1. Introduction

A variety of consumer demands and short cycle of production life spans in custom manufacturing systems trend fast in response to consumer demands without an increase in materials or parts stock. Most traditional scheduling theories and applications view the scheduling problem as static; however, in practice, managers encounter the problem of managing various activities occurring in a workshop. Some problems are dynamic, i.e., a deterministic schedule becomes obsolete due to uncertainties in manufacturing resources, such as machine break and late arrival of materials. Another problem involves the challenge of responding quickly to various consumer orders in dynamic production environments, considering the occurrence of variations in the system, such as order priority and processes that vary in time.

Production scheduling is a complex but extremely important aspect of operation control in operation research, industrial engineering, and management. It is also the basis for key specifications of exact production output in terms of products, dates and quantities, and providing the basis for promising delivery to customers (Jacobs et al. 2011). Job shop scheduling (JSS), known more commonly in practice as shop floor control, involves the sequence of different machines or manufacturing processes for various orders. Sequencing issues on the shop floor involve the set of operation activities that transform real-time information inputs on the status of the production system, including the types of resource states and order flows, such as the variety of order priority, scheduled ship data, associated processing time by workers and equipment, to end item outputs.

This study proposes a procedure to find a feasible solution that minimizes the makespan of JSS to balance the load on machines in parallel, considering machine reliability and resource work schedules. The flow shop contains two parallel manufacturing process flows, each containing multiple manufacturing processes. The occurrence of resources in parallel is common in both manufacturing and service industries; therefore, from theoretical and practical perspectives, it is important to balance the load of resources in parallel in dynamic production environments.

The simulation model is constructed by accounting for the occurrence of variations in the system, such as deviations in the order arrival time, order priorities, and processes that vary in time. Two neural networks are then trained to automatically record training data for each parallel manufacturing process flow. To minimize the average makespan of a variety of orders, neural network trainers are integrated into the simulation model to support decision-making during scheduling optimization. As a result, each order is routed to the production line where the neural network predicts that it will have the lowest makespan.

2. Simulation and machine learning in industry 4.0 environments

Supply chains are across much more complex and interconnected networks in today's Industry 4.0 environment. As supply chains generally account for between 60% and 90% of all company costs, sales and operations plan is expected to provide many improved benefits for all stakeholders based on new ideas and collaborations powered by enhanced information technologies (Vandeput 2021).

At the operational level in the real practice of supply chains, the most gap-bridging concern is with constructing a manufacturing schedule and updating it over time inside the demand fence. Here, demand fence could be the changes of production orders including new production orders or available to promise orders entered. Changes to the plan within a period typically are imperatively required to meet customer requirements.

Alternatively, Industry 4.0 includes terms such as “smart factory” and “smart manufacturing”, redefining the concept of “factory” as a fully connected and automated manufacturing system. In ideal smart factories, autonomous machines can exchange information electronically and continuously. This communication enables symbiotic simulation models to collect more usable data, such as machine processing time, production speed, and maintenance status.

In a dynamic Industry 4.0 environment, planning and scheduling activities focus on how to generate an intermediate and precise plan or how to generate a schedule from computerized information, which include complete representations of operating constraints and custom rules (Smith et al. 2018). Sections 2.1 and 2.2 thoroughly discuss the significant benefits and role of simulation and machine learning in an Industry 4.0 environment.

2.1 Rapid Assessment and Prediction of the Impact of Complex System Processes

Because of the level of automation and autonomy in smart factories, symbiotic simulation in Industry 4.0 environments faces more challenges than previously anticipated. Manufacturing processes in smart factories have become more dynamic and complicated. Complex system processes in smart factories present challenges for operations managers, especially when unanticipated events, such as material delays, machine breakdowns, and system failures, occur. Therefore, different configurations and settings are required to achieve operational flexibility in smart factories. Operations managers must adapt to changes in machine status, priority orders, and scheduling rules. For instance, an arriving high-priority order must be immediately assigned to a machine regardless of other orders that are already in line for processing by the same production line. In addition, when failures or breakdowns occur, a substitute schedule should immediately be assigned to resources in the work-in activities using symbiotic simulation models. Furthermore, the assigned worker must cease their current processing tasks, and a different on-shift worker should be assigned to continue processing the ceased work. It should be noted that symbiotic simulation factories can link physical and virtual environments. As a result, symbiotic simulation and machine learning technologies are the driving methodologies for rapidly assessing and predicting the impact of changes in complex manufacturing systems. Therefore, symbiotic simulation combined with machine learning is prominent in dynamic Industry 4.0 environments and aids in optimizing complex system processes.

Simulation is a powerful tool for evaluating the interactions between machines and optimizing manufacturing systems. In a dynamic Industry 4.0 environment, planning and scheduling activities focus on generating an intermediate and precise plan or schedule from computerized information, which includes complete representations of operating constraints and custom rules (Smith et al. 2018).

Thus, the extensive range of applications of autonomous machines and robotics is a core aspect of simulation in Industry 4.0 environments.

2.2 Integrating Various Data Sources with Symbiotic Simulation

Over the past decades, simulation has played an important role in operations management as a means to evaluate systems, compare alternatives, and optimize configurations. Information technologies are extremely important for improving simulation performance and providing potential benefits to Industry 4.0 implementations. In this regard, advancements in system simulations have propelled simulation processes into a new position as decision-making tools for Industry 4.0 applications.

In the current Industry 4.0 era, powerful computing resources can be used to collect and efficiently share a variety of data types related to customers, orders, and machine operations. Effective data flow can be applied to the simulation modeling of production activities. The difference between simulation objectives in Industries 4.0 and 3.0 relates to the flexibility and accuracy of simulation results due to data requirements and acquisition. Thus, the speed and flexibility of data collection and processing combined with other computing resources are critically important for symbiotic simulation modeling. In other words, although symbiotic systems present a useful system design to represent physical systems, including various types of computing resources, data use methods are needed to integrate different data sources before performing symbiotic simulation models. Technological advancements have made it easier to collect and share large volumes of data, in addition to facilitating its application to models and evaluating various possible scenarios to predict and drive outcomes (Smith, Sturrock, and Kelton 2018).

Over the past decades, an increasing number of real-time operational data have become available to be collected electronically and continually. Artificial intelligence (AI) such as machine learning and simulation have both played an important role in operations management by providing unique advantages in processing and analyzing more usable business data.

Artificial intelligence, such as machine learning, is now making its way into manufacturing. Over the past decades, increasing amounts of real-time operational data have become available electronically and continually. Artificial intelligence has also played an important role in operation management by providing unique advantages for processing and analyzing more usable business data. Buchmeister et al. (2019) provided an overview of major future changes in the production branch triggered by the use of artificial intelligence. Machine learning and pattern recognition software can soon become key factors in factory transformation. Machine learning is commonly used for data analysis, data classification, and forecasting and is responsible for generating ideas for efficient production and supply chain management. Consequently, machine learning has made it easier to analyze large volumes of business data. Thus, the combined use of both technologies is expanding to evaluate the interactions between different resources and optimize manufacturing systems.

Alternatively, production and supply chain activities focus on generating an intermediate and precise plan or schedule from computerized information, including complete representations of operating constraints and custom rules (Sturrock et al., 2018). In a manufacturing environment, scheduling functions must interact with other decision-making functions (Pinedo, 2016). Therefore, simulations are becoming a popular method for the interaction of virtual and physical systems (Gaku et al., 2020). This also means that the simulation requires various data sources, such as parameters and data generated by a machine learning algorithm, to enable better performance prediction of use areas. Therefore, combining the use of both digital technologies and real-time or near-real-time business data to evaluate systems, compare alternatives, and optimize configurations can be a smart way to support production management.

3. Decision-Making Processes of Scheduling Optimization Using Agent-Based Simulation Modeling and Neural Networks

On a day-to-day basis, manufacturing planning and control (MPC) changes the plan for sales and operations into a plan for the production of specific products with the objective of producible products output and timing determined. JSS activities are expected to provide many improved benefits and fundamental roles for MPC. A possible example of the decision-making processes of scheduling optimization using agent-based simulation modeling and neural networks in an Industry 4.0 context is shown in Figure 1. The steps involved in the decision-making process of scheduling optimization using simulation are as follows:

[Step 1]: Defining the baseline measurement. The baseline measurement is provided to compare the performance of in its current state with the performance before neural networks are used to improve how orders are routed. This, in turn, provides an understanding of the effectiveness of neural network models.

[Step 2]: Assembling the relevant data. Preparing the data is responsible for providing appropriate data in step 3. A large amount of data related to specific operations in the system must be collected and applied to estimate the current and future values or states of resources. Data can include information regarding future demand for products, machine status data, and data linked to personal resources.

[Step 3]: Constructing a manufacturing system. In this process, a manufacturing system is constructed using agent-based simulation, in which orders are routed at random to processing lines where resources are allocated to order-seize requests based on the ranking rules of the process logic for each resource.

[Step 4]: A quantity of training data is collected from the simulation model constructed in step 3. At this step, the simulation model is performed to automatically record training data for the machine learning models.

[Step 5]: The neural networks are integrated into the simulation model. In this step, neural networks are trained to predict the makespan if a particular line is selected to route orders to the line with the smallest predicted makespan.

[Step 6]: Evaluate the simulation results obtained from Steps 4 or 5. Here, the audit is reviewed to determine if the production schedule is an appropriate fit for the system and can provide ideas for efficient production planning. If not, step 5 is repeated to make the necessary parameter adjustments for the training process. Occasionally, at step 6, a solution with acceptable performance was found.

[Step 7]: Obtain and output the schedule solution of the manufacturing processes.

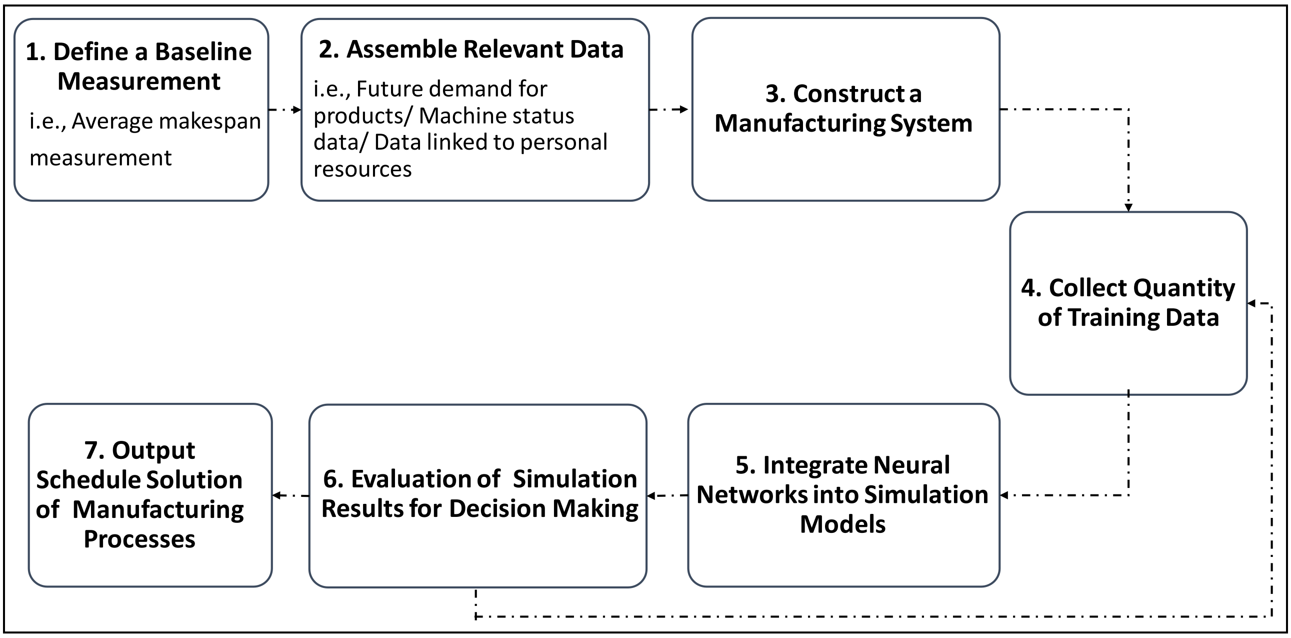

Fig. 1. Decision-making processes of scheduling optimization using agent-based simulation modeling and neural networks in Industry 4.0 environments.

4. Case Study of Scheduling Optimization for a Feasible Production System with Two Parallel Manufacturing Process flows

In an Industry 4.0 environment, communication between the manufacturer's shop floor and customers drives mass customization to be adopted as a production system (Takakuwa 2016). This section introduces an example of scheduling optimization for a feasible production system with two parallel manufacturing process flows in company A to further understand how simulation and machine learning are used in the procedure proposed in Section 3.

As shown in Figure 2, the feasible production system consists of two lines, each with four ordered processing locations. Process 1 of each line uses part 1, and process 2 uses part 2 with the subassemblies from process 1. Processes 3 and 4 have similar process logics with different subassemblies compared to front-end processes.

When orders arrive, they are routed to either Line A or Line B and cannot change their line. The two production lines follow the just-in-time manufacturing method, in which the Kanban can be used to feed parts into the system at a constant rate (Monden, 1983).

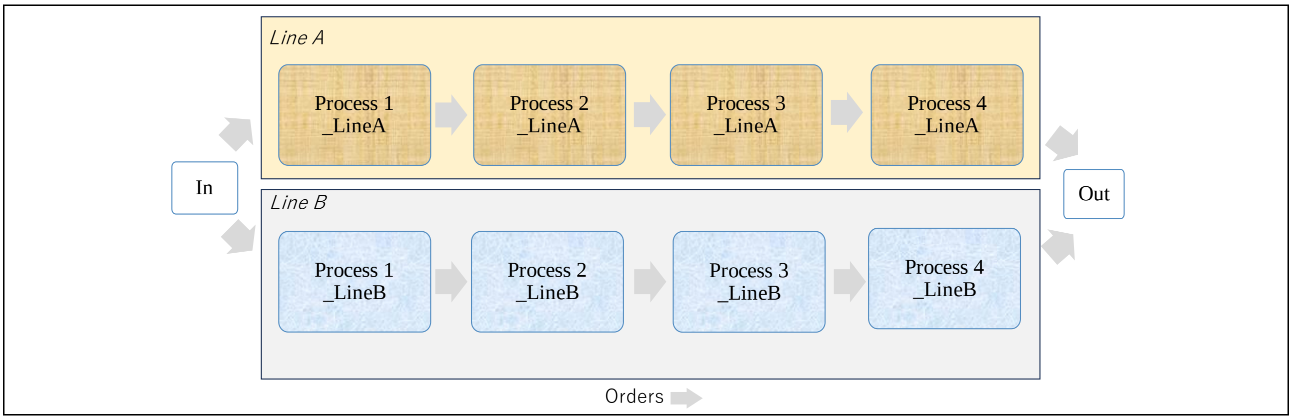

Fig. 2. Parallel manufacturing flow shop.

When orders are processed at the final location on their line, they are transferred to a shipping shoot where they depart to their customers. In this study, the baseline measurement is the average makespan of all orders at step 1 to compare the performance of the production system in its current state with its performance after order routing with processing ranking and sequence. The completion time of the last operation for each order was used to calculate the average makespan of the orders in the following three simulation models:

(a) **Baseline Model**: A baseline average makespan measurement is established for the current state parallel manufacturing process flows.
(b) **Alternative Model**: The defined order priorities are considered and used to evaluate the processing ranking of each order.
(c) **Agent-Based Model**: Neural networks are trained and fed with random data collected by performing the (b) alternative model to obtain the lowest predicted makespan.

In models (b) and (c), the defined order priorities are considered to decide and perform the standardized processing operations for each process at each line, as presented in Table 1. At Steps 2 and 3, if orders are assigned with a defined order priority, the order with the smallest value of the order priority can enter service preferentially when resources are available and one or more orders are waiting. For instance, Order11 with Priority 1 has higher priority than Order12; however, Order01

OrderId	OrderDate	DueDate	Priority
Order01	2023/9/1 8:00	2023/9/8 9:00	1
Order02	2023/9/1 8:00	2023/9/9 9:00	2
Order03	2023/9/1 8:00	2023/9/15 9:00	3
Order04	2023/9/1 8:00	2023/9/11 9:00	1
Order05	2023/9/1 8:00	2023/9/13 9:00	2
Order06	2023/9/1 9:00	2023/9/26 10:00	3
Order07	2023/9/1 9:00	2023/9/13 10:00	1
Order08	2023/9/1 9:00	2023/9/24 10:00	2
Order09	2023/9/1 9:00	2023/9/24 10:00	3
Order10	2023/9/1 9:00	2023/9/17 10:00	1
Order11	2023/9/1 9:00	2023/9/18 10:00	2
…	…	…	…

Tab. 1. Simulation input data of Orders.

takes precedence over Order11 because the order arriving time OrderDate for Order01 is on 2023/9/1 at 18:00, preceding Order11 in the line waiting for processing in either Line A or Line B. Table 2 presents the main task time of each process in the alternative simulation models considered in this study. Each process includes three operations: loading, processing, and unloading parts.

At step 4, orders can be routed to a line at random, allowing random data to be collected before the neural network models are trained. In this study, the simulation models in cases (b) and (c) were used to run simulation replications until the neural networks that trained the data repository equaled the maximum record limit of 1000. Here, the collected data represents the load at each process in the line where the order is routed. For example, an order is routed to Line A. When this occurs, the neural network model associated with Line A will record the load at each process in Line A. The makespan is recorded after the order is completed in process 4. In this study, the simulation models dealt with 18 orders with different order priorities, due dates, and so on.

The neural network models in step 5 are used to construct the makespan predictors of each line. Figure 3 shows the epoch numbers of the training performances, which is

OrderId	ProcessingTimeOfLineA_ Process1_LoadingPart	ProcessingTimeOfLineA_ Process1_Processing	ProcessingTimeOfLineA_ Process2_LoadingPart	…
Order01	Random.Triangular(1,1.5,2)	Random.Uniform(10 , 25)	Random.Triangular(8,10,12)	…
Order02	Random.Triangular(1,1.5,2)	Random.Uniform(30 , 35)	Random.Triangular(6,8,10)	…
Order03	Random.Triangular(2,5,7)	Random.Uniform(30 , 35)	Random.Triangular(6,8,10)	…
Order04	Random.Triangular(2,5,7)	Random.Uniform(10 , 25)	Random.Triangular(6,8,10)	…
Order05	Random.Triangular(1,1.5,2)	Random.Uniform(10 , 25)	Random.Triangular(8,10,12)	…
Order06	Random.Triangular(1,1.5,2)	Random.Uniform(10 , 25)	Random.Triangular(8,10,12)	…
Order07	Random.Triangular(2,5,7)	Random.Uniform(30 , 35)	Random.Triangular(6,8,10)	…
Order08	Random.Triangular(2,5,7)	Random.Uniform(10 , 25)	Random.Triangular(8,10,12)	…
Order09	Random.Triangular(5,7,12)	Random.Uniform(30 , 35)	Random.Triangular(6,8,10)	…
Order10	Random.Triangular(1,1.5,2)	Random.Uniform(10 , 25)	Random.Triangular(6,8,10)	…
Order11	Random.Triangular(1,1.5,2)	Random.Uniform(30 , 35)	Random.Triangular(8,10,12)	…
…	…	…	…	…

Tab. 2. Main task time for each order of each process for alternative simulation models.

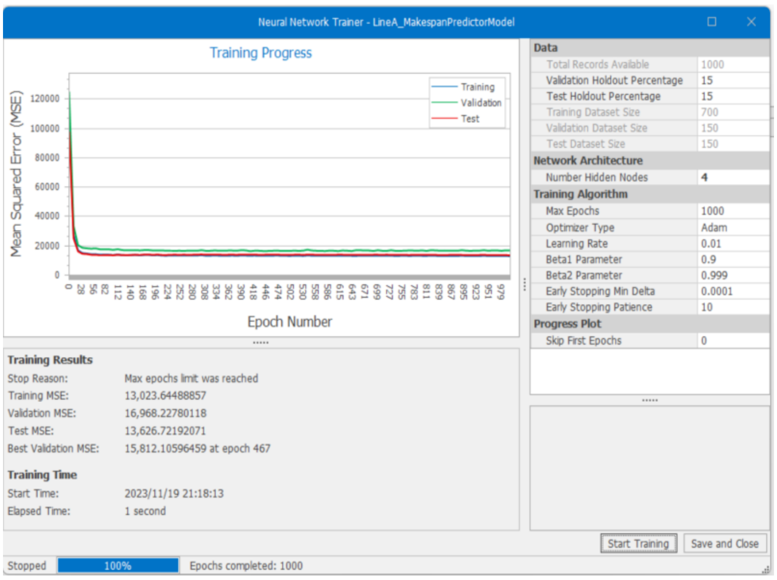

Fig. 3. Epoch number of training performance for Line A.

the number of times the entire dataset was passed through the algorithm in the neural network model of Line A. The neural network models of Lines A and B are trained and then integrated into the simulation models. Based on the expected makespan of each line predicted by the trained neural network models, each line was routed in the order with the lowest predicted makespan. Table 3 presents the simulation results of the average makespan output from the simulation models at step 6. The average makespan for all orders in the current state of the production system at the (a) baseline model is 393.7352 h. The baseline measurement is increased to 394.7151 h in the (b) alternative model after considering the order priorities, thereby allowing the routing group to make intelligent decisions. Finally, the average makespan decreased noticeably in the (c) agent-based model to approximately 382.7665 h. Hence, at step 7, an optimal schedule satisfying all constraints is outputted, as shown in Figure 4. Moreover, the three simulation models provide actional schedules for processing operations for each process at each line. The lowest measure of makespan among the three simulation moods illustrates that the feasible schedule shown in Figure 4 outputted from the (c) agent-based model, which has the best objective value, is the optimal schedule for the production system in this study.

(a) Baseline Model	393.7352
(b) Alternative Model	394.7151
(c) Agent-Based Model	382.7665

Tab. 3. Average makespan of alternative simulation models.

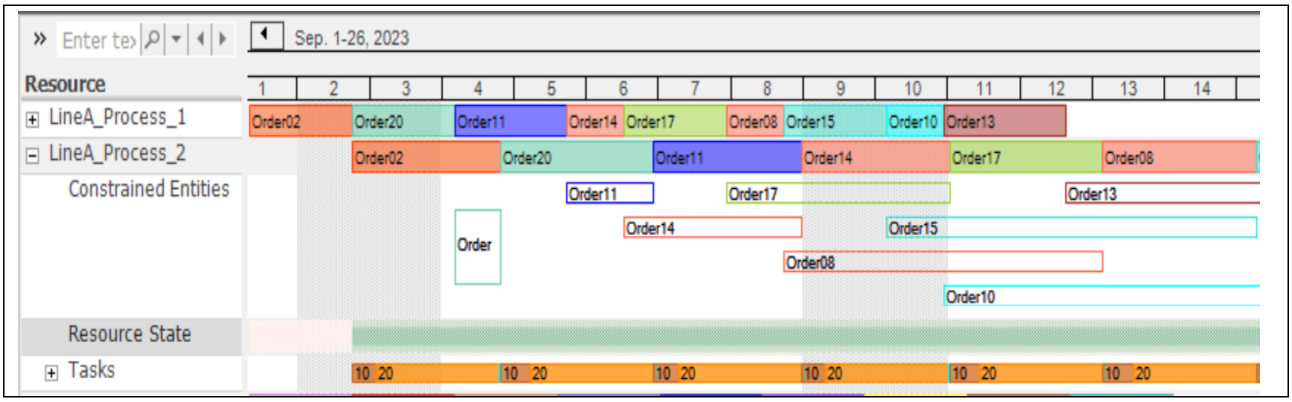

Fig. 4. A part of optimal schedule outputted from (c) Agent-Based Model.

5. Conclusion

In this study, simulation is used to reflect the current state of the production system with two parallel manufacturing process flows. Simulation is also used as a scheduling tool to generate and assess the quality of schedules with objective measurements defined as makespan. To minimize the average makespan of a variety of orders, neural network trainers are integrated into the simulation model to support decision-making during scheduling optimization. The simulation results show that simulation with neural networks can enable better performance prediction of production scheduling.

Moreover, simulation and neural network technological advancements are powerful and effective for the associative use of complicated JSS accounting for the occurrence of variations in the system. A symbiotic simulation driven by real-time or near-real-time operational data sources allows for cooperation between virtual and physical systems to make operational or scheduling decisions under multiple real-world constraints. In future research, the proposed decision-making processes for scheduling optimization using agent-based simulation modeling and neural networks can be used in comparison with other complicated production systems. Based on the defined objective measurement, the profit and cost impacts of different schedules can be tested to identify various feasible alternatives to support the decision-making of JSS.

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