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Demand prediction and optimization of workshop manufacturing resources allocation: A new method and a case study

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ABSTRACT

At present, great changes are taken place in the internal production management and resource allocation model of manufacturers. Under the premise of rational resource allocation, the completion period of products largely depends on the timeliness of resource allocation. The related studies mostly tackle the allocation of a single type of production resources in a single workshop, without considering much about the mutual influence between workshops. Through in-depth research on workshop manufacturing practices, this paper chooses to explore the planning, allocation, and demand prediction of manufacturing resources, which has long been a difficulty in workshop production. The research has great scientific research significance and practical value. The authors designed an algorithm based on the difference of the mean stagnation time of different production processes in the execution process, and used the algorithm to predict the number of production resources required in each period, before formulating the optimal configuration plan. This method is highly reasonable and applicable. After presenting a prediction method for the allocation demand of workshop manufacturing resources, the authors discussed whether the manufacturing resource allocation between different workshops is balanced in a fixed period. Then, a new idea was proposed for collaborative production between machines of different workshops in a specific environment, and an optimization algorithm was put forward to optimize the manufacturing resource allocation to machines facing the operation execution process. Through experiments, the authors compared the utilization rate of material, technological or human production resources in each period, and thereby verified the effectiveness of the proposed algorithm.

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1. Introduction

As consumers demand more and more personalized products, manufacturers are engaged in an increasingly fierce competition. As a result, great changes are taken place in the internal production management and resource allocation model of manufacturers [1-7]. Currently, the main challenges to manufacturers include the diversity of customized products, the small batch size, and the strict delivery period. This requires manufacturers to manage production and allocate resources scientifically and efficiently [8-11].

From the perspective of resource supply, the management department of workshop manufacturing resources must allocate resources rationally, in order to enhance machine utilization, and shorten the completion period [12-19]. Under the premise of rational resource allocation, the completion period of products largely depends on the timeliness of resource allocation.

The demand prediction for workshop manufacturing resources is to build a proper prediction model according to the workshop layout, order quantity, machine production attributes, and internal/external production conditions, and make overall forecast of the allocation demand of workshop manufacturing resources.

Clark [20] developed three models and the corresponding fast heuristics methods to identify production plans and instant setting plans for production lines with switching time. The three methods were tested statically, and then tested based on rolling period. The test results show that the methods differ in demand prediction accuracy, capacity tightness, and period length. Schneider *et al*. [21] described the Markov decision process of production scheduling, and constructed a value function specific to the current demand prediction, which can generate the optimal scheduling decision online. In addition, an industrial application and reinforcement learning approach was developed for generating the similar value function in the field. Experimental results show that value function approximation is effective in both deterministic and noisy environments.

Fiasché *et al*. [22] combined evolutionary algorithm with its quantum version into a hybrid approach. The simulation environment is ideally located inside two factories, partners and use cases of the white'R FP7 FOF MNP Project, with high manual activity to produce optoelectronics products, switching with the use of the new robotic (re)configurable island, the white'R, to highly automated production. Results show that the hybrid approach provided better answers and faster convergence than other methods. In recent years, many enterprises have shifted from single-point production to a more complex manufacturing environment, involving several multi-product facilities.

Ackermann *et al*. [23] proposed a mixed integer linear programming (MILP) model, and applied to the simultaneous material supply and scheduling of multi-site and multi-product intermittent plants with heterogenous parallel units. The applicability and performance of the model was demonstrated with numerical examples. Chernigovskiy [24] introduced ant colony optimization (ACO) to production scheduling, and compared the efficiency of the algorithm with other production scheduling algorithms on real cases. Through the comparison, they summarized the strengths of ACO, and its benefits to the manufacturing process.

The related studies mostly tackle the allocation of a single type of production resources in a single workshop, without considering much about the mutual influence between workshops. To fill the gap, this paper carries out the demand prediction and optimization simulation for workshop manufacturing resource allocation [25-31]. Based on the mean stagnation time of different production processes in the execution process, this paper designs an algorithm to predict the number of production resources required in each period, and formulate the optimal configuration plan. This method is highly reasonable and applicable. Compared with the existing algorithms, our algorithm optimizes the simulation of the allocation of workshop production and manufacturing resources under multiple working conditions, and achieves high application value for improving the workshop scheduling system. Section 2 presents a prediction method for the allocation demand of workshop manufacturing resources. After determining the prediction method, Section 3 discussed whether the manufacturing resource allocation between different workshops is balanced in a fixed period. Section 4 proposed a new idea for collaborative production between machines of different workshops in a specific environment, aiming to obtain the optimal resource allocation plan for minimizing the mean stagnation time during the execution of production operations. In addition, an optimization algorithm was put forward to optimize the manufacturing resource allocation to machines facing the operation execution process, and its flow was illustrated. Through experiments, the simulation tools based on discrete event simulation were compared with the proposed simulation optimization model. The experimental results verify the effectiveness of the proposed algorithm.

2. Demand prediction

In the actual situation of manufacturers, the management department of workshop manufacturing resources does not allocate resources to each workshop, but choose one workshop for resource allocation. Moreover, the resources are only allocated to a workshop when the manufacturing resources is out of balance. Therefore, this paper presents a new prediction method for workshop manufacturing resource allocation, and an index reflecting whether the resource allocation is balanced between workshops. To predict the demand for workshop manufacturing resource allocation, the key is to forecast the variation in the resource demand of each machine in the workshop. Thus, it is necessary to project the cumulative resource demand of each machine, as well as the overall resource demand of the workshop.

The XGBoost-based stacking model was adopted to predict the variation in the resource demand of each machine. On this basis, the resource demand of all machines in a workshop was predicted. Then, the demands of different workshops were added up to obtain the final prediction of resource allocation demand.

In a workshop X, the set of machines is denoted by $R = \{r_1, r_2, \ldots, r_m\}$. Then, the resource demand variation of each machine r_i can be calculated by:

$$\hat{G}_{S_{R_i}}(o) = g_{SMVP}(r_i, o) \tag{1}$$

where, g is the prediction model trained by the corresponding sample set E; o is the time interval. Then, the resource demand variation of workshop X can be calculated by:

$$\hat{G}_{S_X}(o) = \sum_{r_i \in R} \hat{G}_{S_{R_i}}(o) \tag{2}$$

Suppose the predicted resource demand variation of each machine r_i has an error of ε_i. Then,

$$\hat{G}_{S_{R_i}}(o) = G_{S_{R_i}}(o) + \varepsilon_i \tag{3}$$

The resource demand variation of each machine in a workshop can be expressed as:

$$\hat{G}_{S_X}(o) = \textstyle\sum_{r_i \in R} G_{S_{R_i}}(o) + \sum_{i \in m} \varepsilon_i \tag{4}$$

$$\hat{G}_{S_X}(o) = G_{S_X}(o) + \textstyle\sum_{i \in m} \varepsilon_i \tag{5}$$

The resource allocation demand of a workshop can be obtained as:

$$E_X(o) = -\hat{G}_{S_X}(o) \tag{6}$$

The resource allocation demand of a workshop is the sum of the resource demand of each single-point machine. During the summation, the prediction error of each machine is also added up. It is very difficult to eliminate that error. Then, the resource demand variation of workshop X can be calculated by:

The XGBoost-based stacking model was directly applied to forecast the resource demand variation of each machine in a workshop.

$$\hat{G}_{S_X}(o) = g_{SMVP}(X, o) \tag{7}$$

where, g is the prediction model trained by the corresponding sample set E; o is the time interval.

Suppose the predicted resource demand variation of each machine in workshop X has an error of ε. Then,

$$\hat{G}_{S_X}(o) = G_{S_X}(o) + \in \tag{8}$$

The resource allocation demand of workshop X can be expressed as:

$$E_X(o) = -\hat{G}_{S_X}(o) \tag{9}$$

The error of overall prediction is smaller than the cumulative error. Hence, the overall demand prediction of workshop resource allocation achieves an ideal effect.

3. Balance analysis

After determining the prediction method, it is necessary to discuss whether the manufacturing resource allocation between different workshops is balanced in a fixed period. Before the discussion, overall consideration should be given to the future demand variation of manufacturing resources, the maximum quantity of manufacturing resources, and the minimum quantity of manufacturing resources in each workshop.

Let $E = \{e_1, e_2, \ldots, e_m\}$ be the quantity of manufacturing resources corresponding to each machine $R = \{r_1, r_2, \ldots, r_m\}$ in workshop X. Then, the total quantity of manufacturing resources that can be accommodated by workshop X can be calculated by:

$$Y_{Max_X} = \sum_{e_i \in E} e_i \tag{10}$$

The maximum φ_{up} and minimum φ_{down} of the quantity of manufacturing resources can be respectively defined as:

$$\varphi_{up_X} = Y_{Max_X} * \xi_{up} \tag{11}$$

$$\varphi_{down_X} = Y_{Max_X} * \xi_{down} \tag{12}$$

where, ξ_{up} and ξ_{down} are two parameters that control φ_{up} and φ_{down}, respectively.

Let Y_{Max_X} denote the highest resource demand of each machine in workshop X. Then, the maximum and minimum quantities of manufacturing resources can be respectively described by φ_{up_X} and φ_{down_X}, respectively:

$$\phi_{up_X} = Y_{Max_X} * \xi_{up} \tag{13}$$

$$\phi_{down_X} = Y_{Max_X} * \xi_{down} \tag{14}$$

The balance of resource allocation between workshops can be detailed as follows:

(1) If $E_X(o)$ is greater than zero, then workshop manufacturing resources diminish. In this case, when $E_X(o) \leq \varphi_{down_X}$, the manufacturing resource allocation of a workshop is balanced, eliminating the need for replenishing manufacturing resources. When $\varphi_{down_X} < E_X(o) \leq \varphi_{up_X}$, the allocation is out of balance, i.e., the machines are not fully utilized, and manufacturing resources should be replenished immediately to meet the demand $E_X(o)$. When $E_X(o)$, the allocation is still out of balance, but simple addition of manufacturing resources will bring another problem, i.e., the manufacturing resource quantity may far exceed the capacity of machines. Thus, it is necessary to set $E_X(o) = \varphi_{up_X}$.

(2) If $E_X(o)$ is smaller than zero, then workshop manufacturing resources increase. In this case, when $|E_X(o)| \leq \varphi_{down_X}$, the manufacturing resource allocation of a workshop is balanced, eliminating the need for transferring manufacturing resources. When $\varphi_{down_X} < |E_X(o)| \leq \varphi_{up_X}$, the allocation is out of balance, i.e., the machines are unable to handle so many manufacturing resources, and the excessive quantity $|E_X(o)|$ of manufacturing resources should be transferred away immediately. When $|E_X(o)| > \varphi_{up}$, the allocation is still out of balance, but simple reduction of manufacturing resources will bring another problem, i.e., the manufacturing resource quantity may fall far short of the capacity of machines. Thus, it is necessary to set $|E_X(o)| = -\varphi_{up_X}$.

4. Proposed allocation optimization approach

The production tasks of machines are planned by the workshop, and each machine has a fixed production efficiency. When the order quantity increases, the shortage of manufacturing resources may occur easily. This will definitely affect the mean stagnation time during the execution of some operations.

To solve the problem, we proposed a new idea for collaborative production between machines of different workshops in a specific environment, aiming to obtain the optimal resource allocation plan for minimizing the mean stagnation time during the execution of production operations, and avoid the unfavorable state that some machines are busy while some machines are idle. This section details the optimization algorithm was put forward to optimize the manufacturing resource allocation to machines facing the operation execution process.

Fig. 1 lists six functions of the optimization algorithm, including reading and storage of production state data, calculation of machine delay function, visual simulation of machines, calculation of mean stagnation time of each operation, resource allocation optimization for collaborative production, and update of manufacturing resource allocation schedule. The six functions are intercorrelated, and work together to ensure the realization of the optimization objective of manufacturing resource allocation.

Fig. 2 shows the three-layer architecture of the optimization algorithm. The functional display layer mainly realizes the man-machine interaction during the simulation. The main functions on this layer include generation of new allocation plan, display of mean stagnation time of each operation, selection of machines for collaboration request, display of production task planning, and real-time visual simulation of production state. The logical processing layer is responsible for all computations and data processing. It mainly has five functions: processing of production state data, update of unoptimized number of machines, calculation of delay function, calculation of mean stagnation time of each operation, and sorting of delay functions. The data access layer stores the important information collected and calculated by the algorithm, mainly including production state data file, production task database, and resource allocation database. The above architecture connects all functional modules of the algorithm, realizes the target functions, and meets the actual production needs of workshops.

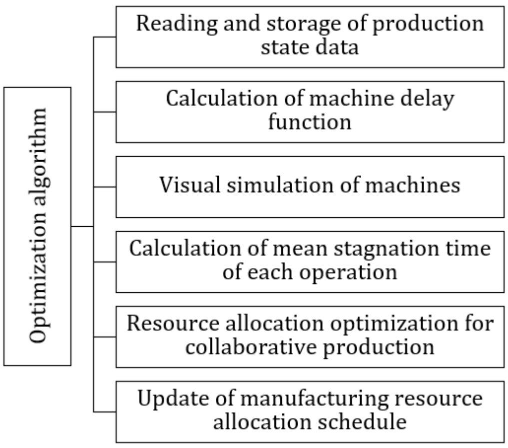

Fig. 1 Some functions of the optimization algorithm

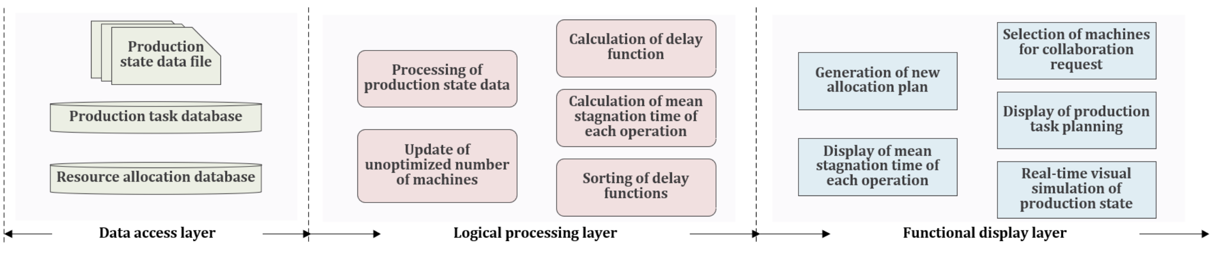

Fig. 2 Architecture of optimization algorithm

The logical processing layer is the core of the algorithm. The structure of this layer is detailed in Fig. 3.

If the initial schedule of manufacturing resources allocation is known, then the manufacturing resources pending allocation optimization will be selected based on the delay function. Next, an optimization model would be constructed for manufacturing resources for simulation and optimization. Then, the allocation of all resources would be optimized iteratively, thereby minimizing the mean stagnation time of each operation in execution.

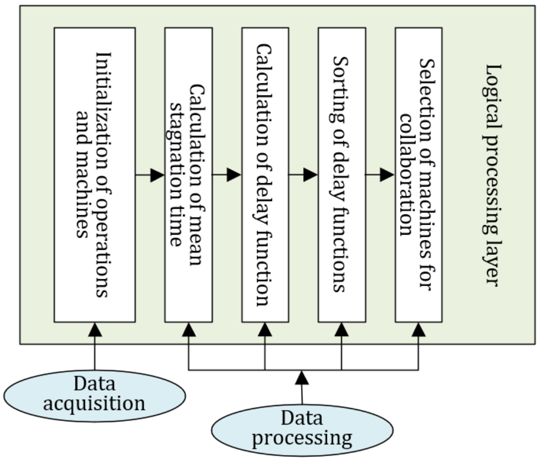

Fig. 3 Structure of logical processing layer

This paper introduces the idea of collaborative production to the optimization algorithm for the manufacturing resource allocation to machines facing the operation execution process: Under certain production conditions, machines with similar production efficiencies can borrow manufacturing resources from each other to execute the same operation, such as to improve the allocation effect of resources throughout the execution process.

After incorporating the above idea, our optimization algorithm breaks the limit of the original schedule of resource allocation: For each operation, only one machine receives manufacturing resources, making it impossible to optimize the resource allocation. Our algorithm can also reasonably reallocate resources to solve the problem that the machines, which are assigned insufficient production tasks, cannot easily respond to the real-time changes of order quantity. In other words, the traditional algorithms are unable to effectively reduce the mean stagnation time of operations, while our algorithm overcomes this limitation.

The collaborative production involves a requestor and a responder. Before optimization simulation, it is important to determine which machines need to request collaboration from others. Two types of machines may become requestors. The first type refers to the machines that cannot timely execute operations, because they are assigned insufficient production tasks. Even if the allocation of a certain type of resources is optimized, these machines have the maximum delay. Then, such machine would request collaboration from others. The second type of machines are selected based on the limitation of the optimization algorithm. If only one machine receives manufacturing resources, and if it has a large delay, then it needs to request collaboration from others.

The responding machine should have the same operations with the requestor, and the minimum delay. The manufacturing resources of the responder needs to be transferred to the requestor. Then, the manufacturing resource allocation is optimized for both parties engaging in collaboration. The above process is implemented iteratively until the algorithm meets the termination condition.

Let m be the current operation; E_m be the set of delay functions of all machines in operation m; E_m^* be the set of delay functions of all machines facing the same operations in operation m; w_m^* be the machine selected from operation m for optimizing the allocation of manufacturing resources; z_m^* be the machine facing the same operations selected from operation m for responding to collaboration requests; ST be the set of all machines; $DE(m)$ be the mean stagnation time of operation m after the optimization of manufacturing resource allocation; v be the unoptimized number of machines during operation m.

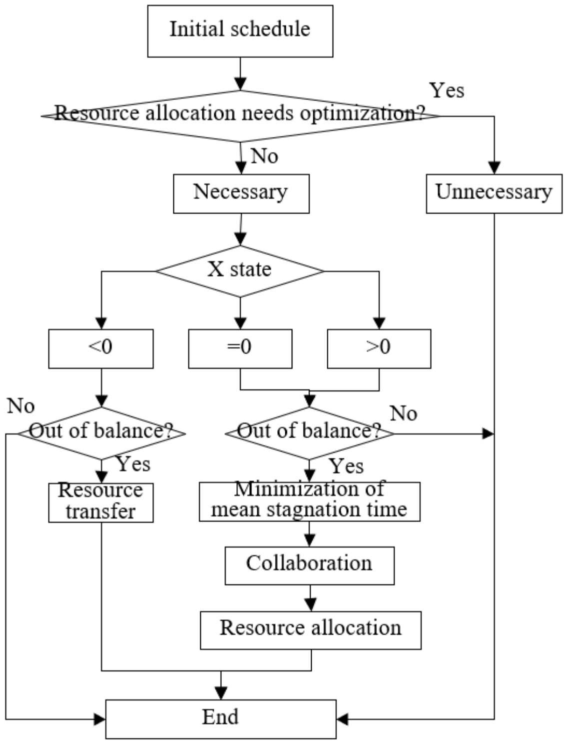

Fig. 4 Steps of our optimization algorithm

As shown in Fig. 4, the specific steps of our optimization algorithm are as follows:

Step 1. In the initial allocation schedule of manufacturing resources, all $\forall w$ satisfy $w \in ST$, i.e., all machines belong to the optimization range of manufacturing resource allocation.
Step 2. The manufacturing resources of all machines are initially allocated as per the original schedule, with $m = 0$, and $w_0^* = \emptyset$.
Step 3. The initial schedule is simulated to solve the current $DE(m)$.
Step 4. For all $w \in ST$, the delay function of each machine is obtained for the current moment.
Step 5. All E_m values are sorted in descending order, with $v = 1$ and $m = m + 1$.
Step 6. If $|v \leq |ST|$, go to Step 7; otherwise, terminate the iteration.
Step 7. The u-th w of $E_{m-1}[v]$ is selected as w_m^*.
Step 8. If $w_m^* = w_{m-1}^*$, all E_m values are sorted in descending order. Then, the machine with the minimum delay z_m^* is selected, and its resources are transferred to w_m^*.
Step 9. The resource allocation is optimized for the requestor w_m^* and the responder z_m^* separately, according to the allocation optimization model.
Step 10. If w_m^* does not receive resources after optimization, $v = v + 1$, and go to Step 6; otherwise, go to Step 11.
Step 11. The new allocation schedule is simulated to obtain the corresponding $DE(m)$.
Step 12. If $DE(m) < DE(m - 1)$, go to Step 4; otherwise, $v = v + k$, and go to Step 6.

5. Simulation results analysis and discussion

Our optimization algorithm for the manufacturing resource allocation to machines facing the operation execution process was verified through multiple simulations. The performance of our algorithm was compared with the traditional manufacturing resource allocation algorithm under the same case, using our independently developed software solution. Table 1 displays the delay functions of all machines in each operation, and the machines needing collaboration in each operation. It can be inferred that the case involves eight operations from the initial allocation schedule of manufacturing resources to the optimal schedule. Some machines requested collaboration in two consecutive operations. These machines lack manufacturing resources severely, failing to meet the real-time demand. Then, out of the machines with the same operations, the machine with the minimum delay should be selected to respond to the collaboration request: their resources should be transferred to the requestor. The calculation results show that the delays of the requestors dropped significantly in a few operations, but the delays of other machines remained largely the same. This verifies the feasibility of collaborative production.

Table 2 shows the stagnation and waiting of each machine in each operation, after the optimization of manufacturing resource allocation. The data in the table further verifies the feasibility of our optimization algorithm. Our simulation optimization model is more effective than the simulation tools of discrete event simulation. It can be seen that the resource allocation to each machine in each operation was improved, and the optimal solution of the allocation schedule was about 50 % lower than the initial solution in terms of stagnation, and 3/4 lower in terms of waiting time. Both stagnation and waiting times were declined from the levels of the traditional resource allocation algorithm.

Figs. 5 and 6 present the quantities of material type and technology/manpower type manufacturing resources pending allocation in each period, respectively. The red and purple lines indicate the resource quantities in the initial situation, and those under the optimal allocation schedule. It can be observed that both types of resources declined significantly, indicating that the new allocation schedule can effectively weaken the obstacles to the flow of manufacturing resources between machines. In addition, different types of manufacturing resources varied in the quantity being processed by machines, owing to the interplay between production efficiencies of different machines in the same workshop.

Figs. 7 and 8 present the machine utilizations of material type and technology/manpower type manufacturing resources in each period, respectively. The red and purple lines indicate the machine utilizations in the initial situation, and those under the optimal allocation schedule. It can be inferred that the machine utilizations improved obviously for both types of resources. In the initial allocation of resources, some machines may be busy, while others may be idle, and some machines were continuously engaged in high-intensity production, owing to the imbalance between resources. These problems were basically eliminated after the allocation optimization.

Table 1 Delay function of each machine in each operation

Machine number	1	2	3	4	5	6	7	8
Operation 0	0.251	0.562	93.154	61.592	0.374	132.651	114.518	0.025
Operation 1	0.284	0.469	152.43	52.618	0.218	41.629	132.542	0.021
Operation 2	0.359	0.526	21.417	62.352	0.348	13.607	152.041	0.029
Operation 3	0.152	0.564	25.168	53.627	0.241	13.521	56.128	0.027
Operation 4	0.137	0.462	24.847	52.195	0.418	11.415	28.419	0.024
Operation 5	0.168	0.641	28.415	14.219	0.482	16.294	25.318	0.023
Operation 6	0.159	0.451	27.462	13.258	0.374	18.492	15.625	0.025
Operation 7	0.156	0.537	18.526	11.416	0.351	15.415	18.207	0.028
Operation 8	0.193	0.412	7.652	8.439	0.318	5.627	18.439	0.051

Table 2 Stagnation and waiting of resources in each operation

	Operation 0	Operation 1	Operation 2	Operation 3	Operation 4
Mean stagnation time	1.251	1.748	1.625	1.205	0..947
Mean waiting time	1.326	1.485	0.718	0.625	0.495
	Operation 5	Operation 6	Operation 7	Percentage of reduction	
Mean stagnation time	0.961	0.815	0.853	52.64	
Mean waiting time	0.357	0.495	0.285	74.51	

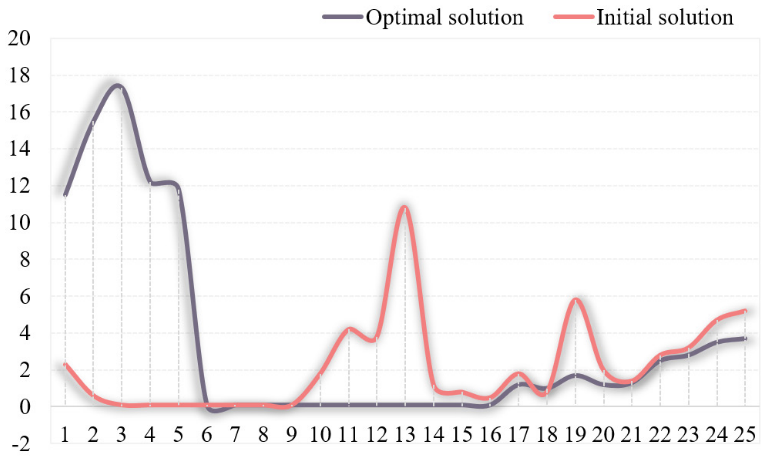

Fig. 5 Quantities of material type manufacturing resources pending allocation

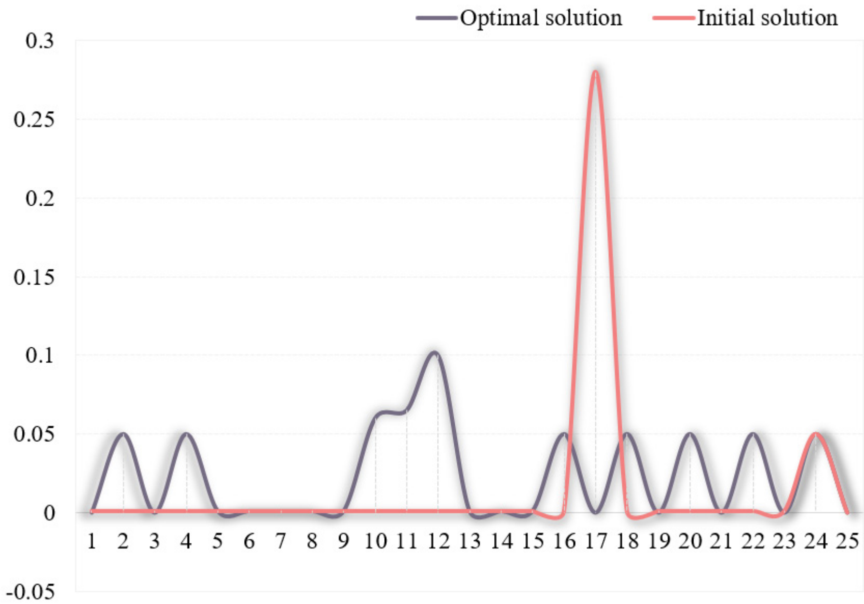

Fig. 6 Quantities of technology/manpower type manufacturing resources pending allocation

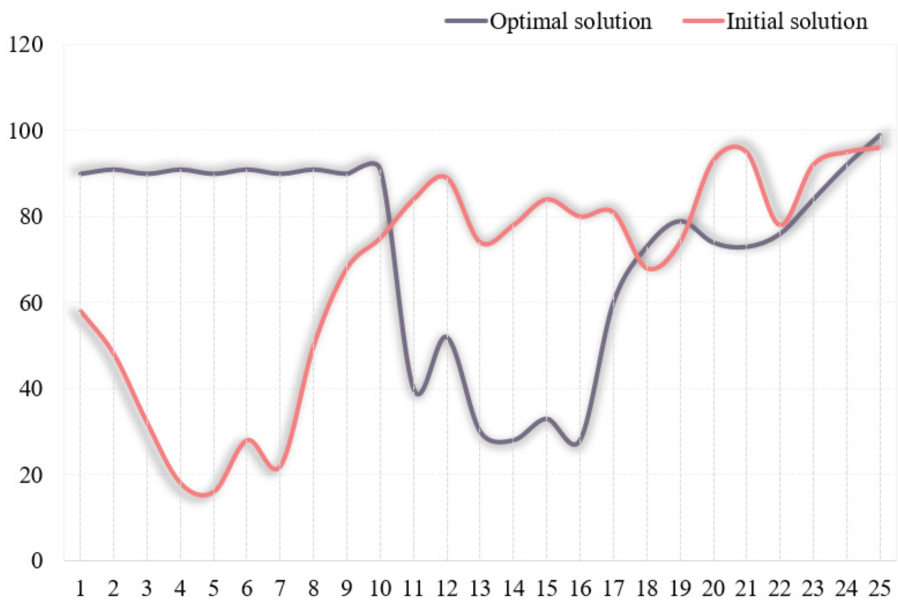

Fig. 7 Machine utilizations of material type manufacturing resources

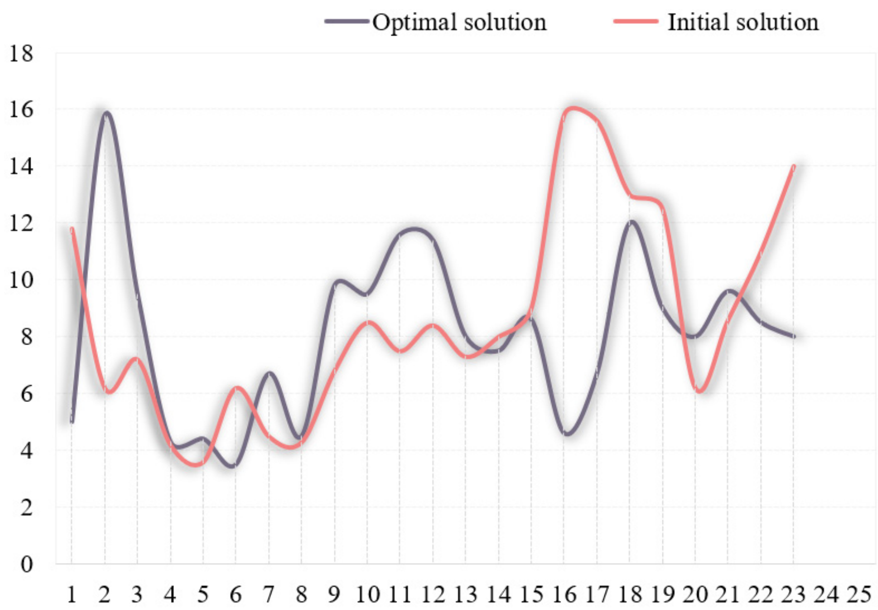

Fig. 8 Machine utilizations of technology/manpower type manufacturing resources

6. Conclusions

This paper carries out the demand prediction and optimization simulation for workshop manufacturing resource allocation. After presenting a prediction method for the allocation demand of workshop manufacturing resources, the authors discussed whether the manufacturing resource allocation between different workshops is balanced in a fixed period. Then, a new idea was proposed for collaborative production between machines of different workshops in a specific environment, and an optimization algorithm was put forward to optimize the manufacturing resource allocation to machines facing the operation execution process. The algorithm flow was detailed.

Through experiments, we displayed the delay functions of each machine in each operation, identified the machines needing collaborative production in each operation, and verified the feasibility of the idea of collaborative production. The effectiveness of our algorithm was further confirmed by obtaining the stagnation and waiting situation of each machine in each operation, after the resource allocation is optimized. Finally, we compared the quantities of material type and technology/manpower type manufacturing resources pending allocation in each period, and contrasted the machine utilizations of material type and technology/manpower type manufacturing resources in each period.

This paper mines the historical dataset of workshop production and manufacturing, researched and established a model and an analysis method, and achieved certain research results. However, the allocation of workshop production and manufacturing resources is affected by various factors, which have intricated correlations. For reasons of dataset and data quality, it is impossible to fully consider and thoroughly explore all the influencing factors and their correlations. In the future, these issues will be considered for further improvement.

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References

[1] Bagheri Rad, N., Behnamian, J. (2022). Recent trends in distributed production network scheduling problem, *Artificial Intelligence Review*, Vol. 55, No. 4, 2945-2995, doi: 10.1007/s10462-021-10081-5.

[2] Rezvani, M.Q., Chaudhary, N., Huseynov, R., Li, M.H., Sharma, A., Jafarova, R., Huseynova, C. (2021). Impact of organisational commitment on employee productivity during Covid-19: Evidence from Afghanistan and India, *Journal of Corporate Governance, Insurance and Risk Management*, Vol. 8, No. 2, 59-74.

[3] Aghighi, S., Niaki, S.T.A., Mehdizadeh, E., Najafi, A.A. (2021). Open-shop production scheduling with reverse flows, *Computers & Industrial Engineering*, Vol. 153, Article No. 107077, doi: 10.1016/j.cie.2020.107077.
[4] Li, Y., Goga, K., Tadei, R., Terzo, O. (2020). Production scheduling in Industry 4.0, In: Barolli, L., Poniszewska-Maranda, A., Enokido, T. (eds.), *Complex, intelligent and software intensive systems, CISIS 2020, Advances in intelligent systems and computing,* Vol. 1194, Springer, Cham, Switzerland, 355-364, doi: 10.1007/978-3-030-50454-0_34.
[5] Febriana, T.H., Hasbullah, H. (2021). Analysis and defect improvement using FTA, FMEA, and MLR through DMAIC phase: Case study in mixing process tire manufacturing industry, *Journal Européen des Systèmes Automatisés*, Vol. 54, No. 5, 721-731, doi: 10.18280/jesa.540507.
[6] Huang, J., Chang, Q., Arinez, J. (2020). Distributed production scheduling for multi-product flexible production lines, In: *Proceedings of 2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, Hong Kong, China, 1473-1478, doi: 10.1109/CASE48305.2020.9216944.
[7] Arena, M., Di Pasquale, V., Iannone, R., Miranda, S., Riemma, S. (2022). A maintenance driven scheduling cockpit for integrated production and maintenance operation schedule, *Advances in Manufacturing*, Vol. 10, No. 2, 205-219, doi: 10.1007/s40436-021-00380-z.
[8] Yang, L., Jiang, G., Chen, X., Li, G., Li, T., Chen, X. (2019). Design of integrated steel production scheduling knowledge network system, *Cluster Computing*, Vol. 22, 10197-10206, doi: 10.1007/s10586-017-1215-7.
[9] Choi, B.-C., Min, Y., Park, M.-J., Kim, K.M. (2020). Production scheduling considering outsourcing options and carrier costs, *Journal of Advanced Transportation*, Vol. 2020, Article ID 7069291, doi: 10.1155/2020/7069291.
[10] Abedini, A., Li, W., Badurdeen, F., Jawahir, I.S. (2020). A metric-based framework for sustainable production scheduling, *Journal of Manufacturing Systems*, Vol. 54, 174-185, doi: 10.1016/j.jmsy.2019.12.003.
[11] Hu, F., Xi, X., Zhang, Y. (2021). Influencing mechanism of reverse knowledge spillover on investment enterprises' technological progress: An empirical examination of Chinese firms, *Technological Forecasting and Social Change*, Vol. 169, Article No. 120797, doi: 10.1016/j.techfore.2021.120797.
[12] Yue, Q., Chen, Z.-L., Wan, G. (2019). Integrated pricing and production scheduling of multiple customized products with a common base product, *IISE Transactions*, Vol. 51, No. 12, 1383-1401, doi: 10.1080/24725854.2019.1589659.doi: 10.1016/j.techfore.2021.120797
[13] Liu, M., Chu, F., He, J., Yang, D., Chu, C. (2019). Coke production scheduling problem: A parallel machine scheduling with batch preprocessings and location-dependent processing times, *Computers & Operations Research*, Vol. 104, 37-48, doi: 10.1016/j.cor.2018.12.002.
[14] Varelmann, T., Erwes, N., Schäfer, P., Mitsos, A. (2022). Simultaneously optimizing bidding strategy in pay-as-bid-markets and production scheduling, *Computers & Chemical Engineering*, Vol. 157, Article No. 107610, doi: 10.1016/j.compchemeng.2021.107610.
[15] Yang, Y., De La Torre, B., Stewart, K., Stewart, K., Lair, L., Phan, N.L., Das, R., Gonzalez, D., Lo, R.C. (2022). The scheduling of alkaline water electrolysis for hydrogen production using hybrid energy sources, *Energy Conversion and Management*, Vol. 257, Article No. 115408, doi: 10.1016/j.enconman.2022.115408.
[16] Maryani, E., Purba, H.H., Sunadi (2021). Analysis of aluminium alloy wheels product quality improvement through DMAIC method in casting process: A case study of the wheel manufacturing industry in Indonesia, *Journal Européen des Systèmes Automatisés*, Vol. 54, No. 1, 55-62, doi: 10.18280/jesa.540107.
[17] Villa, A., Taurino, T. (2018). Event-driven production scheduling in SME, *Production Planning & Control*, Vol. 29, No. 4, 271-279, doi: 10.1080/09537287.2017.1401143.
[18] Aghelinejad, M., Ouazene, Y., Yalaoui, A. (2018). Production scheduling optimisation with machine state and time-dependent energy costs, *International Journal of Production Research*, Vol. 56, No. 16, 5558-5575, doi: 10.1080/00207543.2017.1414969.
[19] Waschneck, B., Reichstaller, A., Belzner, L., Altenmüller, T., Bauernhansl, T., Knapp, A., Kyek, A. (2018). Deep reinforcement learning for semiconductor production scheduling, In: *Proceedings of 2018 29th Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC),* Saratoga Springs, New York, USA, 301-306, doi: 10.1109/ASMC.2018.8373191.
[20] Clark, A.R. (2005). Rolling horizon heuristics for production planning and set-up scheduling with backlogs and error-prone demand forecasts, *Production Planning & Control*, Vol. 16, No. 1, 81-97, doi: 10.1080/09537280412331286565.
[21] Schneider, J.G., Boyan, J.A., Moore, A.W. (1998). Stochastic production scheduling to meet demand forecasts, In: *Proceedings of the 37th IEEE Conference on Decision and Control (Cat. No. 98CH36171)*, Tampa, Florida, USA, 2722-2727, doi: 10.1109/CDC.1998.757865.
[22] Fiasché, M., Liberati, D.E., Gualandi, S., Taisch, M. (2018). Quantum-inspired evolutionary multiobjective optimization for a dynamic production scheduling approach, In: Esposito, A., Faudez-Zanuy, M., Morabito, F., Pasero, E. (eds.), *Multidisciplinary Approaches to Neural Computing, Multidisciplinary approaches to neural computing, Smart innovation, systems and technologies,* Vol. 69, Springer, Cham, Switzerland, 191-201, doi: 10.1007/978-3-319-56904-8_19.
[23] Ackermann, S., Fumero, Y., Montagna, J.M. (2018). Optimization framework for the simultaneous batching and scheduling of multisite production environments, *Industrial & Engineering Chemistry Research*, Vol. 57, No. 48, 16395-16406, doi: 10.1021/acs.iecr.8b03140.
[24] Chernigovskiy, A.S., Kapulin, D.V., Noskova, E.E., Yamskikh, T.N., Tsarev, R.Y. (2017). Production scheduling with ant colony optimization, *IOP Conference Series: Earth and Environmental Science*, Vol. 87, Article No. 062002, doi: 10.1088/1755-1315/87/6/062002.
[25] Wang, Y.J., Wang, N.D., Cheng, S.M., Zhang, X.C., Liu, H.Y., Shi, J.L., Ma, Q.Y., Zhou, M.J. (2021). Optimization of

disassembly line balancing using an improved multi-objective Genetic Algorithm, *Advances in Production Engineering & Management*, Vol. 16, No. 2, 240-252, doi: 10.14743/apem2021.2.397.

[26] Duan, W., Ma, H., Xu, D.S. (2021). Analysis of the impact of COVID-19 on the coupling of the material flow and capital flow in a closed-loop supply chain, *Advances in Production Engineering & Management*, Vol. 16, No. 1, 5-22, doi: 10.14743/apem2021.1.381.

[27] Tian, W., Zhang, H.P. (2021). A dynamic job-shop scheduling model based on deep learning, *Advances in Production Engineering & Management*, Vol. 16, No. 1, 23-36, doi: 10.14743/apem2021.1.382.

[28] Jiang, H., Liu, C.Y. (2019). Scheduling optimization of cloud resource supply chain through multi-objective particle swarm optimization, *International Journal of Simulation Modelling*, Vol. 18, No. 1, 163-174, doi: 10.2507/IJSIMM18(1)CO3.

[29] Janes, G., Perinic, M., Jurkovic, Z. (2017). An efficient genetic algorithm for job shop scheduling problems, *Tehnički Vjesnik–Technical Gazette,* Vol. 24, No. 4, 1243-1247, doi: 10.17559/TV-20150527133957.

[30] Meng, J.L. (2021). Demand prediction and allocation optimization of manufacturing resources, *International Journal of Simulation Modelling*, Vol. 20, No. 4, 790-801, doi: 10.2507/IJSIMM20-4-CO20.

[31] Ojstersek, R., Buchmeister, B. (2021). Simulation based resource capacity planning with constraints, *International Journal of Simulation Modelling*, Vol. 20, No. 4, 672-683, doi: 10.2507/IJSIMM20-4-578.