Production Scheduling in Industry 4.0

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Yuanyuan Li, Klodiana Goga, Roberto Tadei, Olivier Terzo

Abstract Manufacturing processes are dynamic and intensive. Efficient and effective production scheduling is a crucial step to guarantee the competitiveness of manufacturing companies. While production scheduling has been studied in the literature for many years, an advanced optimization strategy is still in the lack of adoption. In the fourth industrial revolution, a set of technologies brings the possibility to transform traditional scheduling approach to the smarter production scheduling system. Motivated to fill in the gap between literature study and practical usage, we introduce a new approach integrated into the operating system under Industry 4.0 context through a case study. Besides demonstrating the new scheduling centered workflow, we also discuss the correlation between saturation and scheduling performance in the aspect of completion time.

1 Introduction

The fourth industrial revolution (Industry 4.0) is coming not only by bringing the concept but also with the implementation in combining a set of technologies (virtual reality, artificial intelligence, big data, robot, 3D printing, cloud computing, IoT, and network security). Manufacturing processes are dynamic and intensive. It is essential to make both effective and efficient production schedules for delivering the final products to customers on time.

In manufacturing production, the scheduling process involves resource assignment and sequencing. In literature, it has been considerably studied ([3],

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[2], [14]). Most works get good performance in terms of completion time with different approaches. However, they tend to focus on literature study or standalone applications ([10]). The successful implementation of the scheduling algorithm involves the correct and abundant data as input. In the dynamic environment, who are the ”diligent” data providers? During the actual implementations in many companies, especially in small and medium enterprises, the scheduling approaches are often based on human experience or simple dispatching criteria. Nevertheless, human effort is limited and prone to errors and dispatching rules are often myopic. To make advanced scheduling algorithms operational is to interact with other manufacturing systems that can feed data to the algorithms. So the lack of adopting digitized and automated systems is a big hurdle for the actual implementation of advanced scheduling systems. In Industry 4.0, there is a growing adoption of new technologies to achieve automation and digitalization. How do these technologies collaborate and enable sophisticated scheduling approaches?

With the motivation to fill in the gap between literature study and practical usage, in Sect. 3.1, we introduce the workflow for developing an effective and efficient scheduling application through a case study.

Besides, in our investigation, we found maximizing saturation of machines is an objective of plant managers in scheduling the productions. The picture that all machines keep working provides the view that we do not waste resources. However, with the fact that timely delivery is a crucial performance in the manufacturing world, does maximizing saturation mean machines are effectively used thus guaranteeing an efficient schedule? In Sect. 3.3, a new study is carried out to show the correlation between saturation and makespan.

Finally, Sect. 4 summarizes the paper and gives some lines for future research.

2 Literature Review

Production scheduling consists of activities conducted in a manufacturing company for managing and controlling the execution of production processes. An optimal schedule respects constraints (e.g., resource, time, and operation sequence) and completes jobs in minimum time. However, finding an optimal sequence is difficult even for a simple manufacturing system with only two identical machines [6]. The approaches range from simple rules to advanced optimization methods.

Job-Shop Problem (JSP) is a representation in scheduling problems with the characteristic that the jobs may have different machine ordering [12]. JSP is defined as follows: given a set of machines m and a set of jobs n, each job j consists of a set of operations processed in sequence. Each operation can be processed on a machine over processing time; the objective is to find a schedule minimizing the total completion time.

Theoretical researches have been done extensively on scheduling. A natural question comes: how do practitioners apply them? In the market, there is a bunch of Advanced Scheduling tools. For example, KATANA[1], which implements priority-based production planning; Aspen Plant Scheduler Family[2], which provides three scheduling solutions to varying degrees of scheduling complexity; Plex[3], which focuses exclusively on manufacturing including the feature on improving utilization of production resources. In commercial schedulers, realtime, efficient usage of production resources, and priority-based strategy appear frequently in the introduction, but the advanced optimization algorithms are not widely advertised and therefore not even implemented. While many plant managers are tempted by the solutions with improving usage of machines (or reducing idle time of machines), does the solution with more saturated machines mean the right solution?

A recent report [4] from World Economic Forum mentions the companies adopting the innovative operating system bring competitive advantages. As is pointed out in the work [8], production schedules should be implemented as part of a total operating system. However, there is still a lack of integration approach elaborated in the research. To fill in the gap, we focus on introducing the production scheduling with the interaction with other components in the new operating system, and what benefits it brings, compared with the traditional approach.

With the two questions below, we elucidate our application in the next sections:

1. in Industry 4.0, how does production scheduling interact with other components in the new operating system?
2. does the solution with more saturated machines mean a good solution?

3 Case Study

In a rubber manufacturing company, there are 15 machines processing production orders from 40 to 60 monthly, and there is only one worker managing setup operation. An order means a job that is composed of 2 operations - printing and assembly. For printing operation, it is processed by a machine and shaped by a fixed mold. Because customers vary from small to big sized companies, the processing time for each operation varies from 10 to over 400 hours.

Every month, according to the orders from the sales management team, the plant manager inserts necessary data (raw materials, quantities, date) and then the Enterprise Resource Planning (ERP) system generates capacity planning by calculating:

- the quantities of raw material to satisfy demand;
- the need for purchasing components to be procured outside;

[1] https:// katanamrp . com/manufacturing - scheduling - software

[2] https://www.aspentech.com/en/products/pages/aspen-plant-scheduler-family

[3] https://www.plex.com/products/manufacturing-operations-management-mom/advanced-planning -production-scheduling-software.html

[4] https://www.weforum.org/whitepapers/global - lighthouse - network - insights - from - the - forefront - of - the - fourth - industrial - revolution/

- requirements of finished products and semi-finished products to be produced

According to the capacity planning, the operator extracts the following information into a Microsoft Excel file:

- production cycle time;
- a set of possible production machines;
- assembling/trimming cycle time.

Then the operator, based on sales volumes, draws up a production plan to the maximum aimed at verifying:

- the saturation of the fleet, direct personnel and assembly department;
- the presence of the raw materials necessary for the production;
- the possible need for additional direct personal and to apply logic to make or buy.

The operator selects the machine for each operation according to the saturation levels, and balances machines by assessing the degree of saturation of the monthly settlement. While executing the production schedule, the running status is checked daily and possibly changed according to the contingent requirements.

Once the daily shift is finished, the production information (date, stopping time of machines and reasons, operator information, product-related information) will be recorded on the payment sheet.

Though the company uses an ERP system to manage raw material, currently, for the production scheduling, it is done by the production manager with spreadsheets and experience. The challenges lie not only in choosing the right machine for each operation but also in sequencing the operations.

Dealing with a complex scheduling problem, to use just human experience is not sufficient. And as complained by the manager, it is unavoidable that human errors frequently appear, which is another reason to encourage more automated processes for limiting human-system interactions. One characteristic of Industry 4.0 is the intensive cooperation between machines and products with less human control [11]. In the following subsection, we propose our scheduling approach and the integration with other modules.

3.1 Scheduling Application

In this section, we address the first question of Sect. 2, i.e., ”in Industry 4.0, how does production scheduling interact with other components in the new operating system?”.

Besides the adopted software ERP, the company is also integrated with the Manufacturing Execution System (MES), which is another representation of advanced industrial automation systems for plant controlling, digital service management, and business functions management of the manufacturing enterprise [15]. The MES is adapted to the characteristics of the company for providing greater ”visibility” to manufacturing operations.

To enable the exchange of information and being stored for better analysis, three types of databases are implemented:

- Common DB: common database, which stores the current data (production orders, maintenance, etc.) shared among ERP, MES, and Planner. For the development, MariaDB[5] - a popular open-source relational database is chosen.
- Realtime DB: realtime database, which enables the retrieval of realtime information of the machines. NoSQL (Not only SQL) database is adopted for managing a large amount of data from any structure. MongoDB[6] - a general-purpose, document-based database serves here.
- Historical DB: the historical data warehouse records historical information coming from the machines to replace the excel file of production payment.

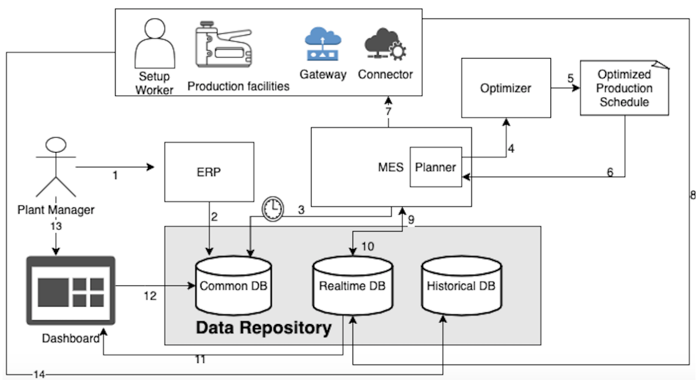

Fig. 1: New Scheduling Workflow

Fig. 1 shows the new workflow. To standardize the communication between various components, EUROMAP 77[7], which describes the interface between injection molding machines and MES for data exchange, is adopted. While the first step keeps the same, the output of ERP will be stored in the Common DB (Step 2). Step 3, MES checks the existence of new data every hour. If there is a new order to be scheduled, Planner - a sub-component of MES will send to Optimizer production requirement (Step 4) extracted from the order. After Optimizer calculates an optimized schedule with the optimization strategy to be introduced in Sect. 3.2, it sends it to Planner (Steps 5 and 6). Step 7, according to the schedule, MES carries out instructions to dispatch individual production units (machines and operators). Because of IIoT devices, realtime communication is possible. Steps 8 and 9, production information (batches of raw materials, processes carried out, operators

[5] https://mariadb.org/

[6] https://www.mongodb.com/

[7] https://www.euromap.org/en/euromap77

involved, quality parameters, etc.) are recorded into Realtime DB and are monitored by MES along the entire production chain. Step 10, when there is an unusual event that happens (e.g., machine breakdown), MES will write to Realtime DB. The dashboard retrieves realtime information from Realtime DB every 5 minutes and updates its content accordingly (Step 11). Step 12, the dashboard retrieves data from the Common DB for displaying the information on the shop floor in detail. Step 13, the plant manager monitors the plant status through the dashboard in realtime. If some machine shows abnormal behavior, the manager could stop the machine directly from the dashboard. Step 14, when the production finishes, the process information, including any report on machine stoppages, is stored into Historical DB. Another point to note is that the dashboard is designed to provide end-users a realtime and centralized update of the production process of the whole company.

Because of the complexity in coordinating the operations involving both people and machines, in the traditional scenario, an experienced manager needs over five hours to obtain a right schedule for a month. Our approach can produce reasonable solutions in concise computational time, which significantly releases human workload and contributes to the company automation.

To summarize, with the new operating system, the benefits lie on the following aspects:

- Centralized Management Systems:
  - the straightforward dashboard and seamless connection between components provide end-users (Plant Manager in this use case) transparency to the entire process and saves time in decision-making;
  - the adoption of database technology enables the data analysis for identifying production failures, bottlenecks, and tracking performance.
- Business processes: the optimized scheduling plan improves the production efficiency (see Sect.3.2)
- People systems: the automated processes reduce both human effort and human errors.
- IIoT systems:
  - the modernized IIoT system builds the connection between plant and end-users in realtime;
  - the flexible devices enable us to add new functions in a matter of weeks.

3.2 Scheduling Problem and Optimization Strategy

Through on-site investigation, the company processes are modeled as a variation of JSP: Flexible Job Shop Problem (FJSP) with sequence-dependent setup times and limited resources. Being flexible is because different products follow different production routes. Limited resources mean limited setup workers and machines.

In our research, we adapted the approach for solving FJSP. Here we briefly explain the workflow. We start with Genetic Algorithm [3] to provide a set of randomly created but feasible solutions as a population. Then we select solutions based on the roulette wheel selection algorithm, which selects potentially useful solutions according to their fitness. The selected solutions will be operated by the genetic operators crossover and mutation to generate new solutions. Then each of the generated new solutions will be ”educated” by Tabu Search [7]. ”Education” here means to improve the quality of solutions by deriving potentially better solutions from the neighbors. For readers who are interested in the detailed analysis or mathematical modeling, please refer to [13].

3.3 Comparison with Original Production Approach

The second question of Sect. 2, i.e., ”does the solution with more saturated machines mean a good solution?” is addressed below.

In [1], the utilization rate of the equipment u_i is calculated as follows

$$u_i = 1 - \frac{idle\ time}{available\ time}. \tag{1}$$

Here, we assume for saturation s_i the same conceptual definition of utilization but modified to be aligned with the production settings (the percentage of effective hours that the machine is working, compared to the maximum possible processing hours from the orders). The reason that we use saturation rather than utilization is to avoid the ambiguity. As written in [9], various definitions of utilization exist in manufacturing: percentage of the shift that the machine is working, identical definition to operator utilization, etc. We recall readers that each product can only be produced with a particular set of machines. When products to be processed are different (in terms of type and quantity), the running hours for the machines are also different. The tabular data on the left of Table 1 shows an instance composed of 3 products to produce in the time horizon H. MID means ID of the machine chosen to process the product, and $MachineAlternative$ means the other machines which can be used to process the product. For the data on the right of Table 1:

- AvailableT: the available time of the machine in the time horizon H;
- MaxT: the maximum time to be used, which is calculated according to the ordered products. For example, the machine with ID 12 can be used for all the three products, so the MaxT is the summation of the time equalling 242.
- Usage: the actual time assigned to the machine. e.g, the machine numbered 12 is assigned to product 3, so the usage is 30.
- Saturation s_i: defined as the saturation rate of machine i, calculated as follows

$$\frac{Usage}{min(MaxT, AvailableT)} \tag{2}$$

Table 1: The Example of Mappings from Product to Machines (left) and the Machine Saturation (right)

Product	ProcessT	MID	MachineAlternative
1	42	24	12, 14
2	170	21	12, 14
3	30	12	16

MID	AvailableT	MaxT	Usage	Saturation
12	240	242	30	0.125
14	240	212	0	0
16	240	30	0	0
21	240	170	170	1
24	240	42	42	1

Following [1], let S denote the overall saturation rate of the machines. With Q machines, S is calculated by

$$S = \frac{1}{Q} \sum_{i} s_i \quad i = 1, \ldots, Q \tag{3}$$

To show the correlation between makespan and average machine saturation, we worked on three instances collected from the factory. For each instance, we calculated ten different scheduling solutions with the optimization strategy mentioned before, and the solutions may result in different makespans. For each solution, the overall saturation rate is calculated as introduced before and then filled into the column *Mean* in Tables 2 and 3. The column *Std* indicates the standard deviation measuring the dispersion of the saturation rate over all the machines. The results provided in Table 2 are calculated with the objective in minimizing makespan, and the ones in Table 2 are maximizing saturation.

The three sub tables in each of Tables 2 and 3 are representing the makespan and saturation respectively from the three instances. The subtables from Tables 2 and 3 on the same position (i.e. left, center and right) match the same instance.

Comparing them, we can see while makespans in Table 2 are much smaller, the saturations are also generally smaller. In Table 3, while saturations are bigger, they do not get smaller makespans back. We can infer that maximizing saturations of machines does not account for a good performance in time saving.

Table 2: Makespans and Saturation Rates for 3 Instances with the Objective in Minimizing Makespan

Makespan	Mean	Std
482	0.82	0.22
499	0.82	0.21
515	0.81	0.27
522	0.82	0.27
523	0.82	0.24
527	0.83	0.28
540	0.83	0.29
547	0.83	0.27
551	0.84	0.27
551	0.83	0.28

Makespan	Mean	Std
498	0.80	0.20
499	0.75	0.20
504	0.73	0.27
504	0.76	0.22
505	0.77	0.19
508	0.75	0.25
522	0.74	0.27
522	0.75	0.20
544	0.76	0.22
545	0.76	0.25

Makespan	Mean	Std
474	0.77	0.29
494	0.77	0.28
498	0.74	0.33
499	0.75	0.35
500	0.77	0.28
501	0.77	0.30
502	0.76	0.30
507	0.75	0.32
513	0.76	0.26
515	0.75	0.29

Table 3: Makespans and Saturation Rates for 3 Instances with the Objective in Maximizing Saturation

Makespan	Mean	Std
580	0.82	0.25
609	0.84	0.30
728	0.97	0.35
750	0.91	0.33
645	0.88	0.31
582	0.84	0.26
754	0.91	0.33
643	0.84	0.28
665	0.88	0.32
582	0.83	0.25

Makespan	Mean	Std
710	0.81	0.24
806	0.86	0.26
756	0.89	0.30
695	0.87	0.20
632	0.75	0.22
817	0.89	0.31
529	0.77	0.20
597	0.82	0.22
982	0.93	0.35
673	0.82	0.26

Makespan	Mean	Std
875	1.06	0.45
733	1.04	0.37
953	1.05	0.43
960	1.04	0.45
684	0.90	0.26
814	0.97	0.36
705	0.95	0.30
733	0.95	0.32
816	0.97	0.37
702	0.97	0.33

4 Conclusions and Future Direction

To improve the competitiveness of manufacturing companies, the ability to quickly responding to the requirements of customers is one of the key success factors. To have the ability, not only a well-designed scheduling algorithm is necessary. Also, a revolution of the operating system to incorporate the scheduling system is a must.

As observed, companies tend to plan the schedule with the mind saturating machines leads to higher efficiency, the result showed in Sect.3.3 proves a higher saturation rate does not mean smaller makespan. So instead of aiming to saturate machines maximally, machine assignment and operation sequence should be arranged effectively, and an appropriate scheduling algorithm can achieve the goals.

Through our study, we realize though advanced scheduling algorithms provide good schedules, they cannot be performed well without sufficient coordination from workers. As pointed out by the paper [16], conventional optimization algorithms tend to overlook human behavioral deviations (workers deviated over 5.8% of packages from the algorithmic prescriptions in order packing instruction problem). From [4], [5], we can see IoT paves the path in stimulating the engagement of people. Meanwhile, an optimization algorithm can guarantee a company pays a minimum cost to achieve the goal. How to use similar ideas to improve labor efficiency thus scheduling efficiency? Next, the focus on human-centric aspects could be conducted to make advanced scheduling operations more operational.

Acknowledgements This research was partially supported by the Plastic and Rubber 4.0 (P&R4.0) Research Project, POR FESR 2014-2020 - Action I.1b.2.2, funded by Piedmont Region (Italy), Contract No. 319-31. The authors acknowledge all the project partners for their contribution.

References

[1] Better M, Glover F (2017) White paper: Complex production scheduling: models, methods and industry case studies
[2] Blazewicz J, Ecker KH, Pesch E, Schmidt G, Weglarz J (2013) Scheduling computer and manufacturing processes. springer science & Business media
[3] Della Croce F, Tadei R, Volta G (1995) A genetic algorithm for the job shop problem. Computers & Operations Research 22(1):15–24
[4] Fadda E, Perboli G, Tadei R (2018) Customized multi-period stochastic assignment problem for social engagement and opportunistic IoT. Computers & Operations Research 93:41–50
[5] Fadda E, Perboli G, Tadei R (2019) A progressive hedging method for the optimization of social engagement and opportunistic iot problems. European Journal of Operational Research 277(2):643–652
[6] Garey MR, Johnson DS (1975) Complexity results for multiprocessor scheduling under resource constraints. SIAM journal on Computing 4(4):397–411
[7] Glover F, Laguna M (1998) Tabu search. In: Handbook of combinatorial optimization, Springer, pp 2093–2229
[8] Graves SC (1981) A review of production scheduling. Operations research 29(4):646–675
[9] Hagan P, Leonard R (1974) Strategies for increasing the utilization and output of machine tools. In: Proceedings of the Fourteenth International Machine Tool Design and Research Conference, Springer, pp 67–78
[10] Harjunkoski I, Maravelias CT, Bongers P, Castro PM, Engell S, Grossmann IE, Hooker J, Méndez C, Sand G, Wassick J (2014) Scope for industrial applications of production scheduling models and solution methods. Computers & Chemical Engineering 62:161–193
[11] Ivanov D, Dolgui A, Sokolov B, Werner F, Ivanova M (2016) A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0. International Journal of Production Research 54(2):386–402
[12] Lawler EL, Lenstra JK, Kan AHR, Shmoys DB (1993) Sequencing and scheduling: Algorithms and complexity. Handbooks in operations research and management science 4:445–522
[13] Li Y, Carabelli S, Fadda E, Manerba D, Tadei R, Terzo O (2019) Integration of machine learning and optimization techniques for flexible job-shop rescheduling in industry 4.0. DAUIN-Politecnico di Torino Internal Report
[14] Ouelhadj D, Petrovic S (2009) A survey of dynamic scheduling in manufacturing systems. Journal of scheduling 12(4):417
[15] Romero D, Vernadat F (2016) Enterprise information systems state of the art: Past, present and future trends. Computers in Industry 79:3–13
[16] Sun J, Zhang D, Hu H, Van Mieghem JA (2019) Predicting human discretion to adjust algorithmic prescription: A large-scale field experiment in warehouse operations. Available at SSRN 3355114