Dynamic Production Scheduling Modeling and Multi-objective Optimization for Automobile Mixed-Model Production

Zhenyu Shen, Qian Tang, Tao Huang(✉), Tianyu Xiong, Henry Y. K. Hu, and Yi Li

State Key Laboratory of Mechanical Transmissions, Chongqing University, Chongqing 400044, China
thuang@cqu.edu.cn

Abstract. Due to inventory redundancy problem caused by automakers mixed-model production mode, a practical scheduling modeling and multi-objective optimization strategy is presented to increase production and inventory efficiency in this paper. Numerous factors including the general assembly shop, the painting shop, and linear buffer between two workshops have been considered, and a novel dynamic production scheduling model is proposed to achieve three optimization goals: (i) equalize parts consumption rate in the general assembly shop so changes in parts inventory can be predicted; (ii) reduce color switching frequency in the painting shop's production queue; (iii) reduce waiting time in car body's buffer zone. Based on this model, an embedded heuristic algorithm with NSGA-2 (No-domination Sorting Genetic Algorithms-II) is employed to solve multi-objective optimization problem. Simulations are finally conducted, when compared with a traditional algorithm, the results are obviously better than traditional algorithm, which validate effectiveness of the proposed model and optimization algorithm.

Keywords: Shop scheduling · Inventory control · Multi-objective optimization Genetic algorithm

1 Introduction

Due to end customers' diversified demands, more companies have adopted production by order strategy, resulting in multiple types of products are collinearly produced on mixed-model production lines. In consequence, wide variety of parts need to be assembled which results in higher inventory cost. When formulating a production plan, the amount of parts inventory needs to be known, so production sequence can be reasonably arranged. Since production flow sequence determines parts usage sequence,

Foundation items: This work was supported in part by the Key Technology Research and System Integration of Discrete Intelligent Manufacturing Workshop, China (No. cstc2016zdcy-ztzx60001), the Fundamental Research Funds for the Central Universities of China under Grant 2018CDXYJX0019, and the National Nature Science Foundation of China under Grant 51805053 as well as Grant 51575069.

K. Li et al. (Eds.): ICSEE 2018/IMIOT 2018, CCIS 924, pp. 25–33, 2018.
https://doi.org/10.1007/978-981-13-2384-3_3

optimizing production queue can help to balanced parts consumption ratio. The purpose of equalization is to reduce fluctuations in consumption rate. This not only increases the robustness of production line, it is also possible to predict the consumption rate of parts, which is the key to keeping inventory at a low level. Through the strategy of milk run [1], stocks will eventually reach a dynamic balance, and it will ultimately achieve the goal to reduce inventory costs.

Prior to the use of intelligent algorithms, most of production scheduling was done manually. Shop scheduling problem is a typical NP-hard problem with exponential explosion characteristics [2], and it is difficult to find the optimal solution relies on manual scheduling. However, the emergence of intelligent algorithms solves this problem. The results filtered by tens of millions of iterations are often much better than the results of manual scheduling [3].

Therefore, this article introduces a dynamic scheduling model that covers the general assembly shop, the painting shop, and painted body storage (PBS) which is a buffer zone connects the two shops. Parts inventory in the general assembly shop will dynamically change as time goes. The optimization goal of the general assembly shop is to equalize the consumption rate of various parts as much as possible while ensuring each car can be assembled on time; the painting shop is to reduce the number of color switching in production queue and lower spraying cost; and PBS is to rearrange the production queues coming out of the painting shop, and to reduce waiting time of vehicles in the buffer zone, under the premise of meeting the general assembly shop's requirements. The NSGA-2 has been selected to achieve these multiple optimization goals. This algorithm has a reliable performance in solving multi-objective optimization problems and is widely used [4].

2 Mathematical Model

Many car companies are currently running on order production mode. An order information represents a specific model of car. In the workshop, an order i corresponds to a list of parts M_i, so the optimization of production queue is essentially the optimization of $\{\mathrm{M}_i\}$. Pre-definition is mandatory for each model of car. Considering extensibility of the mathematical model, 42 different models are predefined, shown in Table 1.

Table 1. Configuration table.

Model	Number of configurations	Number of colors
A	5	4
B	4	3
C	3	2
D	2	2

Meanwhile, a collection of parts lists required for 42 models $\left\{\mathrm{M} : \mathrm{M}_{i,j} \in \mathrm{M},\ i \in N_1, j \in N_2\right\}$ is defined, and all parts are assigned to 10 stations. Dissimilar parts have been divided into 4 categories, totaling 52, as shown in Table 2.

Table 2. Parts list.

Station	Number of parts	Type	Station	Number of parts	Type
1	10	T1	6	4	T3
2	3	T2	7	3	T2
3	1	T4	8	4	T3
4	4	T3	9	3	T2
5	10	T1	10	10	T1

Among them, T1 are customized parts that can be used only for the specified model of the specified configuration, such as seats and engines. T2 are common parts in different car models that can be used only for the specified configuration, like in various electronic auxiliary systems. T3 are common parts in different configurations that can be used only for specified models, like interior trimming panels and wheels. T4 are common parts for all vehicles, like different fasteners.

For the general assembly shop, the parts consumption speed needs to be more balanced. The theoretical consumption rate of each part is

$$\mathrm{E}V_j = \bar{V}_J = \frac{N_1}{\sum_{i=1}^{N_1} \mathrm{M}_{i,j}} \tag{1}$$

Deviation between actual consumption rate and theoretical consumption rate is the optimization goal of the general assembly shop.

$$\min\ f_1 = \frac{\sum_{j=1}^{N_2} \left(V_j - \bar{V}_J\right)^2}{N_1} \tag{2}$$

For the painting shop, reducing the frequency of color switching can reduce coating costs. The number of color switching can be expressed as

$$S_i = \begin{cases} 0, & i = 1 \\ 0, & \mathrm{color}(i) = \mathrm{color}(i-1) \\ 1, & \mathrm{color}(i) \neq \mathrm{color}(i-1) \end{cases} \tag{3}$$

Therefore, the optimization goal of the painting shop is

$$\min f_2 = \sum_{i=1}^{N_1} S_i \tag{4}$$

There are many kinds of buffers for connecting the general assembly shop and the painting shop, linear, circular, backward and so on [5]. In general, waiting buffer time of car body is always proportional to the optimization effect of buffer. Therefore, linear buffer has been selected for our model.

For PBS, the less time car bodies are waiting in PBS, the more efficient PBS will be. The waiting time can be expressed as

$$W_i = \begin{cases} i(i'), & i' = 1 \\ i(i'), & i(i'-1) < i(i') \\ i(i'-1), & i(i'-1) \geq i(i') \end{cases} \tag{5}$$

So, the optimization goal of PBS is

$$\min f_3 = T_{t2} \sum\nolimits_{i'=1}^{N_1} (W_i - i) \tag{6}$$

3 NSGA-2 and Heuristic Buffer Algorithm

Three optimization objectives have strong correlations and involve many variables. Changes in any workshops' production queue will affect another workshop queue and buffer. Therefore, a multi-objective optimization algorithm is necessary. The typical multi-objective evolutionary algorithms are NSGA-2, PESA-2 and SPEA-2. Each of these three algorithms has its advantages and disadvantages. The advantage of NSGA-2 is that it has high operational efficiency and good distribution of solution sets in low-dimensional problems; its disadvantage is that the diversity of solution sets is not ideal in high-dimensional problems. The advantage of PESA-2 is that the convergence of its solution is very good; but the disadvantage is that the selection operation can only select one individual at a time, the time consumption is very large, and the class diversity is not good. The advantage of SPEA-2 is that it can obtain a well-distributed solution set, but its clustering process takes a long time to maintain diversity, and the operating efficiency is not high.

In order to balance the running time with the quality of reconciliation, NSGA-2 was eventually selected. Besides, we have designed a heuristic algorithm that can directly calculate the downstream shop queue within constraints of the linear buffer, based on the queue of upstream shop and the optimization goal of downstream shop which are embed it in the NSGA-2.

The heuristic algorithms are divided into inbound rules and outbound rules. The inbound rules are as follows:

1. If the last car in a lane has the same color of the waiting car, enter the lane.
2. Enter a lane with least car.

Its outbound rules are as follows:

1. In the waiting outbound car, select the same color as the last outbound car.
2. Unless the number of waiting cars in PBS is greater than *M*, otherwise there is no car outbound.
3. When the number of waiting cars in PBS is greater than *M*, select the lane with the highest number of cars, and outbound.

It should be pointed out that the general assembly shop is set to be the upstream workshop and the painting shop as the downstream workshop. The reason is that the optimization of the painting shop is simpler than the general assembly shop. A simple heuristic algorithm can be selected if it achieves a good optimization effect. By adjusting the parameter *M*, we can balance with waiting time and optimization effect. When *M* is larger, there will be reduce color switching in the painting shop production queue, but longer waiting time in PBS.

For the actual buffer, its inbound and outbound order are opposite to our algorithm. When the algorithm is used in the real buffer, actual outbound rule will be different to the outbound rule that we have designed, but inbound rule stays the same. The actual outbound has only one rule: outbound is order specified from the general assembly shop.

This heuristic algorithm needs to be embedded in NSGA-2, and through iterative filtering, the scheduling plan which meets our optimization goals can be identified. Algorithm flow chart is shown in Fig. 1.

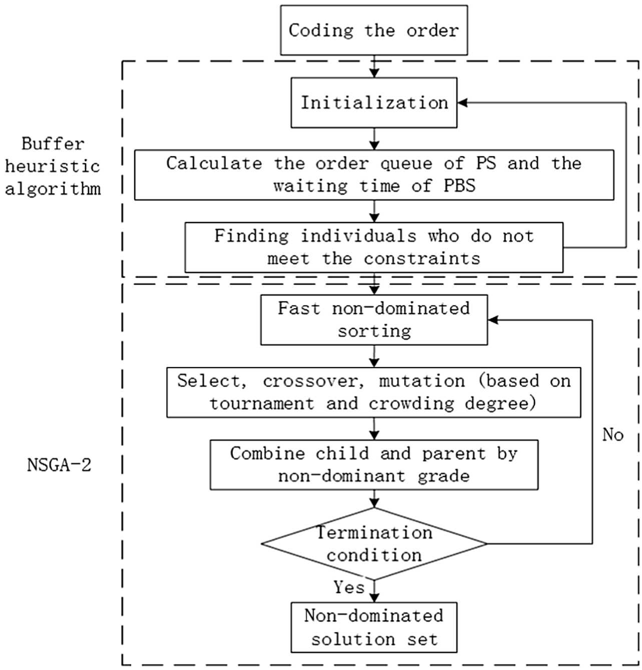

Fig. 1. Algorithm flow chart.

4 Simulation Examples

The simulated data is based on the production plan of 1,000 cars in a car factory within one day. In addition, a traditional algorithm is designed to compare with the above algorithm. This traditional algorithm is actually applied to the factory, rely on PLC control and will determine the inbound and outbound sequence of body in PBS according to a fixed priority. Both that embedded heuristic algorithm based on NSGA-2 and traditional algorithms are programmed by Matlab.

Due to computational complexity, the production plan has been divided into 10 equal proportions smaller plans, so only one portion (100 cars) production queue needs to be calculated. Then connect them end to end in a cyclic manner to get the total production queue, so this total production queue is "equalized". Inventory changes of parts should conform to the rule in Fig. 2.

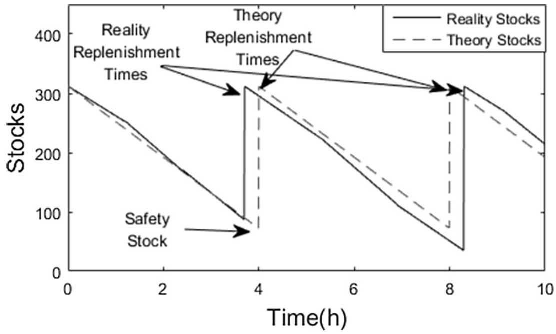

Fig. 2. Inventory Changes.

Two example was run 50 times. The operating environment of the program is Intel Xeon CPU E3-1240 3.50 GHz, and the RAM is 32 GB. The average time of operation of embedded heuristic algorithm was 278.8 s, which is sufficient for a one-day production plan of a car factory. And traditional algorithm uses the same production sequence of painting shop with embedded heuristic algorithm.

The results of the two algorithms are shown in Tables 3 and 4 respectively.

Table 3. Non-dominated solution set of embedded heuristic algorithm.

Pareto solution	Optimization goal		
	f_1	f_2	f_3
P_1	2203.3	11	700
P_2	2209.8	11	500
P_3	2297.4	11	450
P_4	2309.6	10	900
Average	2582.7	12.8	810

Taking P_3 as an example, cars are numbered from 1 to 42 according to their models, configurations and colors. Starting from the time when first car arrives at station 10 in the general assembly shop, record the time $t = T_0$. Then parts inventory status and production line status at $t = T_1 = T_0 + 10 * T_{t1}$, $t = T_2 = T_1 + 10 * T_{t1}$ are respectively as shown in Figs. 3 and 4.

The solution obtained by the traditional algorithm have lower waiting time, but the consumption rate of parts is very uneven. The consumption rate of parts will directly

Table 4. Corresponding solution set of traditional algorithm.

Solution	Optimization goal		
	f_1	f_2	f_3
P'_1	7354.8	11	450
P'_2	8785.4	11	450
P'_3	7927.5	11	450
P'_4	7651.7	10	450
Average	7885.1	12.8	450

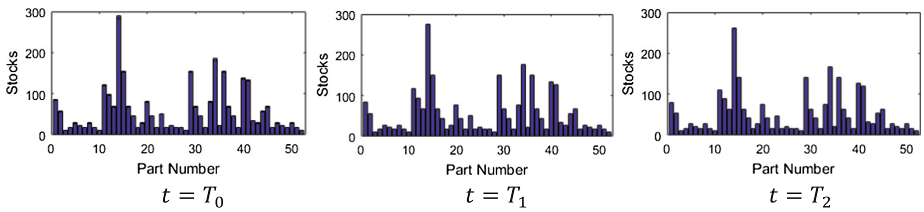

Fig. 3. The status of inventory at different times.

affect the inventory of the assembly shop, but the waiting time will not be. In order to study what negative impact the waiting time would have on the production line, some inspection work was done.

When observing the results of the calculation, an unrealistic situation was discovered. The results show that when waiting time is bigger, a kind of defect is more likely to appear. This defect will result vacancies at the production queue of the general assembly shop. The reason for this defect is that there are fewer bodies available in the PBS when the queue is first started. If there is no body that meets the outbound rules, there will be a vacancy in the assembly shop queue.

To avoid this situation, the production speed of the painting shop needs to be greater than the general assembly shop, and the M value increases over time for a short period of time when the queue is just starting to run. When the available car body in the PBS is sufficient, the M value no longer increases.

Actually, as long as the car body can meet the constraints of continuous outbound, they are all equivalent regardless of the waiting time. If the embedded heuristic algorithm can ensure continuous outbound car body in PBS. The traditional algorithms do not have obvious advantages in Optimization goal 3. Instead, there is a clear disadvantage in optimizing goal 1. It can be considered that the embedded heuristic algorithm has a comparative advantage over the traditional algorithms.

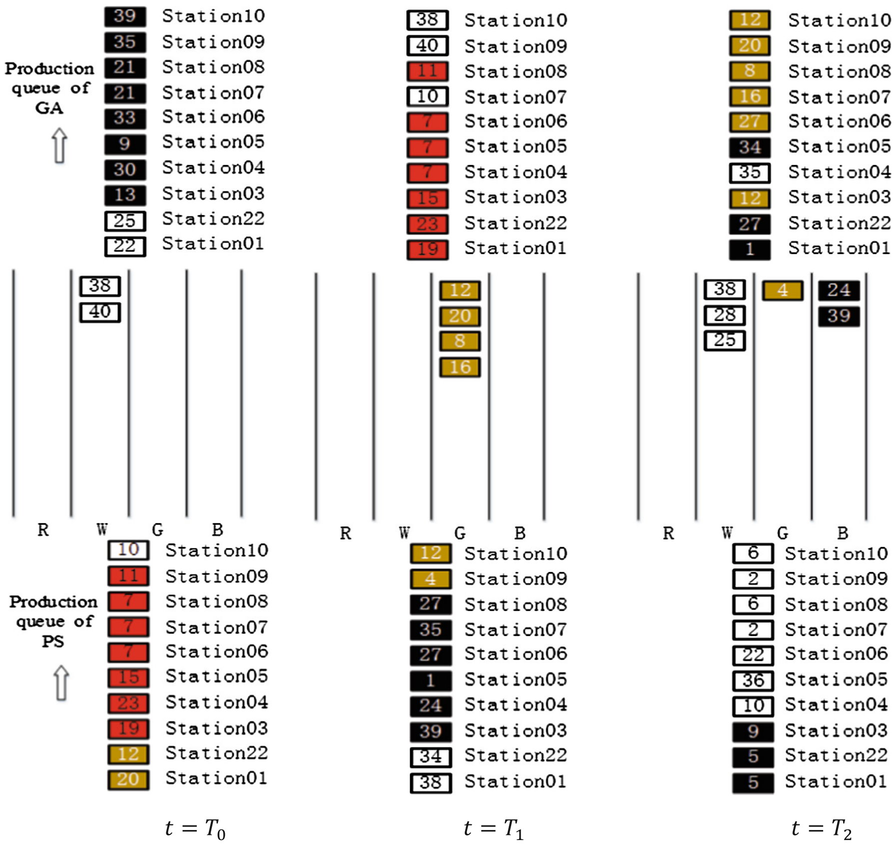

Fig. 4. The status of the production line at different times.

5 Conclusion

In this paper, a dynamic scheduling model is proposed for automobile mixed-model production. By scheduling the sequence reasonably, this model can balance the consumption rate of parts in the general assembly shop, reduce the number of color switching in the painting shop, and improve reordering efficiency of the linear buffer. When compared with a traditional algorithm, the result is obviously better than the traditional algorithm. In addition, this is beneficial to achieve a more accurate inventory control and sequence tracking by monitoring status of parts inventory and production queues. It can be known for any order, it is where and how to complete, and even which batch of parts are being used at the time. The value calculated by this model can be serve as an important reference for the automakers who want to reduce their production cost.

References

1. Sadjadi, S.J., Jafari, M., Amini, T.: A new mathematical modeling and a genetic algorithm search for milk run problem. Int. J. Adv. Manuf. Technol. **44**(1–2), 194–200 (2009)
2. Jalilvand-Nejad, A., Fattahi, P.: A mathematical model and genetic algorithm to cyclic flexible job shop scheduling problem. J. Intell. Manuf. **26**(6), 1085–1098 (2015)
3. Soleimani, H., Kannan, G.: A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks. Appl. Math. Model. **39**(14), 3990–4012 (2015)
4. Deb, K.: A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-2. Lect. Notes Comput. Sci. **1917**, 849–858 (2000)
5. Chen, GY: Research on buffer design and resequence in automobile production line. Huazhong University of Science and Technology (2007)