Wenwen Lin
Yuejun Zhang

INTEGRATED PRODUCTION AND MAINTENANCE PLANNING FOR FLOW LINE SYSTEMS

Summary

This study extends the investigation of the capacitated lot-sizing problem to the production and maintenance planning in unreliable flow line systems. An integrated modelling framework is proposed with the aim of seeking a cost-optimal plan for both production and maintenance. In the model, preventive maintenance is scheduled to avoid unplanned failures, and corrective maintenance is carried out in any machine in which an unplanned failure occurs. A regression-based approximation approach was introduced to calculate the production time under random failures. Then, the integrated planning model can be solved by any commercial optimization software. The numerical example demonstrates that the integrated model guarantees the effectiveness of the production and maintenance plan. It also showed that the buffer capacity has significant effects on the capacity utilization.

Key words: *production planning; maintenance; flow line system; simulation; polynomial regression*

1. Introduction

It is natural that a machine deteriorates and then fails during production. Any machine failure might lead to the whole production line breaking down. Therefore, maintenance is necessary to restore machines. In the past several decades, many maintenance and replacement models have been proposed from the perspective of cost, availability or reliability [1, 2].

Integrating maintenance into the production planning has been highlighted already in the paper by Weinstein and Chung [3]. Gu et al. [4] searched for hidden maintenance opportunities to perform maintenance tasks without affecting the system throughput. Arab [5] investigated a maintenance scheduling problem which incorporates the real-time information from workstations and work-in-process inventories.

1.1 Integrated planning of production and maintenance

Due to stoppages caused by machine failures and maintenance, the efficiency decreases over the planning horizon. When machine failures occur, corrective maintenance (CM) is carried out to replace the worn-out component and keeps machines operational. Preventive

maintenance (PM), on the other hand, is scheduled in advance to avoid unplanned failures and it reduces the cost caused by stoppages.

Weinstein and Chung [3] proposed an aggregated production planning (APP) model with maintenance operations at multiple levels and motivated a considerable number of follow-up papers listed in **Table 1**. Mark "√" means that corresponding maintenance is used while "−" means that such maintenance is not used. Most of the problems considered in the mentioned papers can be described as a special case of the capacitated lot sizing problem (CLSP), which is a classical production planning model that contains the essential requirements for the planning of the batch production. These CLSP models are conceived as single-stage systems in terms of the system configuration. Further, Ramezanian et al. [6] proposed an integrated planning model for a multi-level production system. However, the machine capacity was tackled separately.

Table 1 Literature about integrated planning of production and maintenance

Literatures	Year	Model	PM	CM	System configuration
Weinstein and Chung [3]	1999	APP	√	√	Parallel machines
Aghezzaf et al. [7]	2007	CLSP	√	√	Single machine
Aghezzaf and Najid [8]	2008	CLSP	√	√	Parallel machines
Nourelfath et al. [9]	2010	CLSP	√	√	Multi-state system
Najid et al. [10]	2011	CLSP	√	√	Single machine
Nourelfath and Châtelet [11]	2012	CLSP	√	√	Multi-state machine
Fitouhi and Nourelfath [12]	2012	CLSP	√	√	Single machine
Alaoui-Selsouli et al. [13]	2012	CLSP	√	√	Single machine
Machani and Nourelfath [14]	2012	CLSP	√	√	Multi-state system
Lu et al. [15]	2013	CLSP	√	−	Single machine
Wang [16]	2013	CLSP	√	√	Single machine
Yalaoui et al. [17]	2014	CLSP	√	√	Parallel machines
Fitouhi and Nourelfath [18]	2014	CLSP	√	√	Multi-state system
Zhao et al. [19]	2014	CLSP	√	√	Single machine
Fakher et al. [20]	2015	CLSP	√	√	Parallel machines
Fakher et al. [21]	2015	CLSP	√	√	Parallel machines
Aghezzaf et al. [22]	2016	CLSP	√	√	Single machine
Beheshti-Fakher et al. [23]	2016	CLSP	√	√	Single machine
Hnaien et al. [24]	2016	CLSP	√	√	Single machine
Erfanian and Pirayesh [25]	2016	APP	√	√	Parallel machine
Nourelfath et al. [26]	2016	CLSP	√	−	Single machine
Shamsaei and Vyve [27]	2016	CLSP	√	−	Single machine
Fakher et al. [28]	2017	CLSP	√	√	Parallel machines

Many papers deal with multi-stage systems without considering machine maintenance. Abdul-Kader [29] provided a planning model that incorporates the capacity constraints from the operational level. To estimate the capacity, machine failures were treated as fictive products, and then the model could be converted into a linear programming model. Diaz and Handl [30] considered a real-world production planning problem, where a hybrid optimization approach with simulation and genetic algorithm was used to support decision making.

1.2   Optimization approaches

Simulation-based approaches take advantage over analytical approaches in the production and maintenance planning. They are applied by adjusting non-deterministic parameters iteratively according to the simulation results, until the target values of the performance indicators are reached. Caggiano et al. [31] combined the CLSP optimization and system simulation by implementing a feedback loop involving the capacity. Chu et al. [32] formulated a bi-level program, where the planning and the scheduling problems are solved iteratively via service level constraints. Ponsignon and Mönch [33] evaluated a planning algorithm for master planning while taking the execution level into account. The simulation-based optimization improves the feasibility of the production plan, but the computational time is never short due to the iteration of simulation.

Apart from the simulation-based approaches, some approximation approaches are developed to address the complexities as well. Mehrjoo and Bashiri [34] proposed a decision support tool for production planning based on the multivariate statistical methods, including the principal component analysis and logistic regression. Stricker et al. [35] considered regression models for predicting an expected reject rate based on the recent system status, thus enabling a robust planning with volatile reject rates. In order to get a robust production plan, Gyulai et al. [36] took the capacity requirements as a general function of the assembled products in the simulation. These papers showed that some approximation approaches could be used in the production planning of some cases instead of simulation-based approaches. What is more, the former approach is always more efficient than the latter.

1.3   Outline

In an unreliable flow line system, analytic approaches failed to calculate the production time for any given lot, while simulations are time-consuming. The contribution of this paper can be summarized as follows: (i) a mathematical model for CLSP-M with both PM and CM considered in an unreliable flow line system is proposed; (ii) a regression-based approximation approach for capacity constraints is introduced, and then the model can be solved by any commercial optimization software.

The remainder of this paper is structured as follows: Section 2 gives the problem description and the integrated modeling framework. Section 3 introduces the regression-based approximation approach and proves its accuracy. A numerical example is given in Section 4 to validate the effectiveness of this modelling approach. In Section 5, conclusions are drawn and new research directions are discussed.

2.   Problem description

In the CLSP-M model, PM and CM are introduced and need to be coordinated with the production tasks. The aim is to generate a cost-efficient plan for both production and maintenance.

2.1   Integrated planning of production and maintenance

Consider a flow line consisting of M machines and $M-1$ buffers, as shown in **Fig. 1**. The line produces a set of products over a finite planning horizon of T periods. The flow line consists of failure-prone machines arranged in series. Machines are economically and structurally independent.
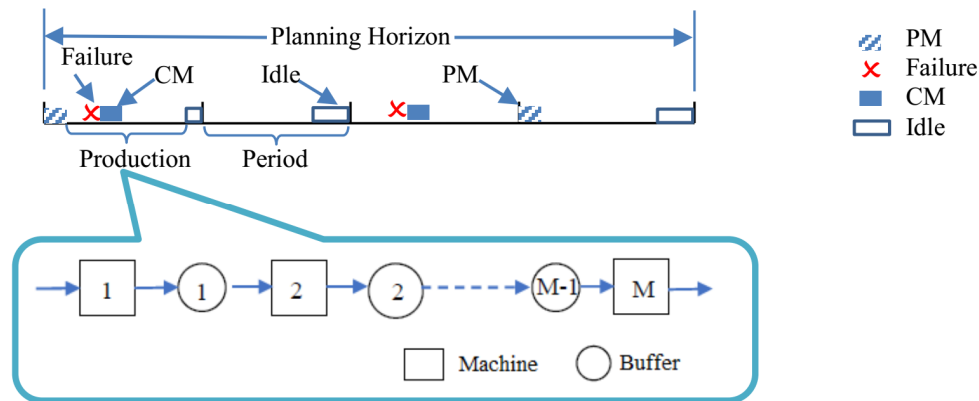
Fig. 1 Production and maintenance operations within a planning horizon

The following assumptions are made in this paper:

1) Each period has a deterministic demand for each kind of product to be satisfied.
2) All periods have the same length.
3) The set-up is carried out when switching from one kind of product to another.
4) There is no initial stock or backorder/shortage for any product.
5) The first machine is never starved and the last machine is never blocked.
6) At each stage, the finished products are released piece by piece and constitute the lot at the end.
7) The products in the buffer storages follow the first-in-first-out (FIFO) rule.
8) The processing time and the repair time for each machine are constant and predetermined.
9) The processing time of a product is a unit time.
10) Each machine deteriorates with an increasing failure rate, and the mean-time-to-failure (MTTF) follows a Weibull distribution.
11) Whenever a machine has a failure, CM is initiated and the machine is recovered to the initial state.
12) PM is scheduled at the beginning of some production period considering varying workload, and the production line is as good as new after PM.
13) The whole lot is completed on the flow line during the same period.

2.2   Model formulation

The integrated planning of production and maintenance in the flow line is modelled as a CLSP-M model. The following notations are used in the model.

Constants

N	number of products
B	a number which is greater than the ideal yield of products in a period when no failure occurs and no maintenance is scheduled

Indices

i	product index ($i = 1, 2, \cdots, N$)
t	planning period index ($t = 1, 2, \cdots, T$)
m	machine index ($m = 1, 2, \cdots, M$)

Parameters

d_{it}	demand for product i at the end of period t
K	length of the production period
h_{it}	holding cost per unit of i at the end of period t
c_{it}	production cost per unit i in period t
s_{it}	set-up cost of producing product i in period t
c_s^p	PM cost of the production line
c_m^c	CM cost of machine m
t_s^p	PM duration for the production line
t_m^c	CM duration for machine m

Variables

y_{it}	binary variable that is equal to 1 if the set-up of product i occurs in period t; otherwise, it is 0.
I_{it}	inventory level of product i at the end of period t.
x_{it}	quantity of product i produced in period t.
u_t	binary variable is equal to 1 if PM is performed at the beginning of period t; otherwise, it is 0.
w_{mt}	expected failure number of machine m in period t.
z_t	flow line age counted by the quantity of produced products
Q_{it}	production time of x_{it} products in period t, and CM is hidden in the production.

Function

r_m	failure rate of machine m.

The mathematical model is given as follows.

The objective function of the model is shown in Equation (1) :

$$\sum_{i=1}^{N}\sum_{t=1}^{T}(s_{it}y_{it} + c_{it}x_{it} + h_{it}I_{it}) + \sum_{t=1}^{T}c_s^p u_t + \sum_{m=1}^{M}\sum_{t=1}^{T}c_m^c w_{mt} \tag{1}$$

The model is subjected to Eqs (2)-(7):

$$x_{it} + I_{i,t-1} - I_{it} = d_{it}, \forall i \in \{1,2,...,N\}, \forall t \in \{1,2,...,T\} \tag{2}$$

$$x_{it} \le By_{it}, \forall i \in \{1,2,...,N\}, \forall t \in \{1,2,...,T\} \tag{3}$$

$$\sum_{i=1}^{N}Q_{it} + u_t t_s^{pm} \le K, \forall t \in \{1,2,...,T\} \tag{4}$$

$$z_t = (1-u_t)z_{t-1} + \sum_{i=1}^{N}x_{it}, \forall t \in \{1,2,...,T\} \tag{5}$$

$$w_{mt} = \int_{(1-u_t)z_{m,t-1}}^{z_{mt}} r(\tau)_m \, d\tau, \forall m \in \{1, 2, \cdots, M\}, \forall t \in \{1, 2, ..., T\} \tag{6}$$

$$x_{it}, I_{it} \geq 0, y_{it}, u_t \in \{0, 1\}, \forall i \in \{1, 2, ..., N\}, \forall t \in \{1, 2, ..., T\} \tag{7}$$

The objective function (1) is composed of system set-up cost, production cost, inventory holding cost, PM cost and CM cost. Constraint (2) ensures the material balance in the production periods for each product. Constraint (3) relates the production variables to the binary set-up variables. Constraint (4) is the capacity constraint, which indicates that the time for production and PM should not be longer than K. Equation (5) derives the effective machine age at the beginning of each period, while Equation (6) calculates the expected failure number. Constraint (7) relates to non-negativity and integrality constraints.

2.3   Capacity constraint

As we can see in constraint (4), the capacity constraint requires simulating the production time of a given production lot under random failures. The simulation procedure is shown in **Fig. 2**.

Notations

j	product index in x
p_{jm}	start time of product j on machine m
q_{jm}	depart time of product j on machine m
B_m	capacity of intermediate buffer after machine m
τ_{jm}	age of machine m after processing product j
v_{jm}	= 1, if a failure occurs during the processing of product j on machine m, otherwise, $v_{jm} = 0$

Product j is processed on machine m after it departs machine $m-1$ and product $j-1$ departs machine m; that yields

$$p_{jm} = \max\{q_{j,m-1}, q_{j-1,m}\} \tag{8}$$

If machine m is not blocked, q_{jm} depends on p_{jm}, the processing time and the potential failure; otherwise, it is equal to the depart time of product $j-1-B_m$ on machine $m+1$ (Eq. (9)).

$$q_{jm} = \max\{p_{jm} + 1 + v_{jm}t_m^c, q_{j-B_m-1,m+1}\} \tag{9}$$

Failure occurrence can be determined by the randomly generated failure instant φ_{mf} and the machine age τ_{jm}.

Q_{it} is equal to the depart time of the last product in the lot on the last machine (Eq. (10)).

$$Q_{it} = q_{jm}, j = x, m = M \tag{10}$$

Input: machine number, processing time; failure distribution, CM duration, production quantity, buffer size

Output: production time

Step 1: generate a two-dimensional array of φ_{mf}

Step 2: calculate $p_{jm} = \max\{q_{j,m-1}, q_{j-1,m}\}$

Step 3: if $\tau_{j-1,m} < \varphi_{mf} < \tau_{jm}$, assign 1 to v_{jm} and $f+1$ to f; otherwise, assign 0 to v_{jm}

Step 4: calculate q_{jm} using Eq. (9) and assign $\tau_{j-1,m} + a_{im}$ to τ_{jm}

Step 5: if $m<M$, assign $m+1$ to m, then go to Step 2; if $m==M$ and $j<x$, assign 1 to m and $j+1$ to j, then go to Step 2; if $m==M$ and $j==x$, assign q_{jm} to $Q(x_{it})$, output is generated. End the procedure.

Fig. 2 Simulation procedure of the production time

3. Regression-based approximation approach

Instead of running multiple simulations during the optimization of the CLSP-M model, a "black box" approach for calculating the production time is introduced. The objective in the "black box" approach is to find a model which describes production time with regression analysis and then decouples the simulation procedure and the model optimization. For a single machine following a Weibull lifetime distribution $W[\beta_m, \eta_m]$, the expected production time $\Psi(\bullet)$ can be regressed as follows:

$$\psi(x) = x + (\frac{x}{\eta_m})^{\beta_m} c_m^c \tag{11}$$

where $\Psi(x)$ is the expected production time, x is the quantity of produced products, and β_m is the polynomial degree.

In prior research, β_m is usually assigned a small value (i.e. first-order polynomial). The reason is that the variation of x_{it} is always kept at a low level, which means that the value of β_m has less impact on the regression result [37]. Thus, a lower polynomial degree is sufficient for regression.

Consider a production line; any failure causes variations in stages which are compensated by buffer storages. In that case, the polynomial degree and the coefficients are adjusted to improve the regression performance. A second-order polynomial is adapted for regression, as shown in Eq. (12).

$$\psi(x) = a_1 x + a_2 x^2 + \varepsilon \tag{12}$$

In the proposed model, Q_{it} can be replaced by $\Psi(z_t) - \Psi((1-u_t)z_{t-1})$. Then, the constraint (4) can be re-represented as follows:

$$\psi(z_t) - \psi((1-u_t)z_{t-1}) + u_t t_s^{pm} \leq K_t \tag{13}$$

Using Eq. (13) instead of Eq. (4), the model can be solved by commercial solvers or heuristics.

The performance of the polynomial regression is examined in different configurations. Suppose that there are 1, 000 products to be processed by an unreliable flow line system with 10 machines. As shown in **Table 2**, the machine parameters are randomly generated: $\beta_m \in U(1,3)$, $\eta_m \in U(500,700)$, $t_m^c \in U(10,50)$. The flow line system with different

configurations (B_m = 0, 5, 10) is simulated using the procedure shown in **Fig. 2**, and each procedure runs 500 times.

Table 2 Machine parameters

m	1	2	3	4	5	6	7	8	9	10
η_m	618	684	627	548	540	644	587	641	516	552
β_m	2.3	1.5	2.9	1.3	2.9	1.5	1.1	2.5	1.9	1.1
t_m^c	40	21	35	16	23	22	18	40	50	17

The simulation process was coded by C# in a personal computer using a 64-bit Windows 10 operating system, a Dual-Core CPU, and an 8-GB RAM. As shown in **Fig. 3**, the average production time converges in tens of simulations. With confidence interval α = 0.05, all the trials have the same simulation error ε < 0.001, which indicates the high accuracy of the simulation results.
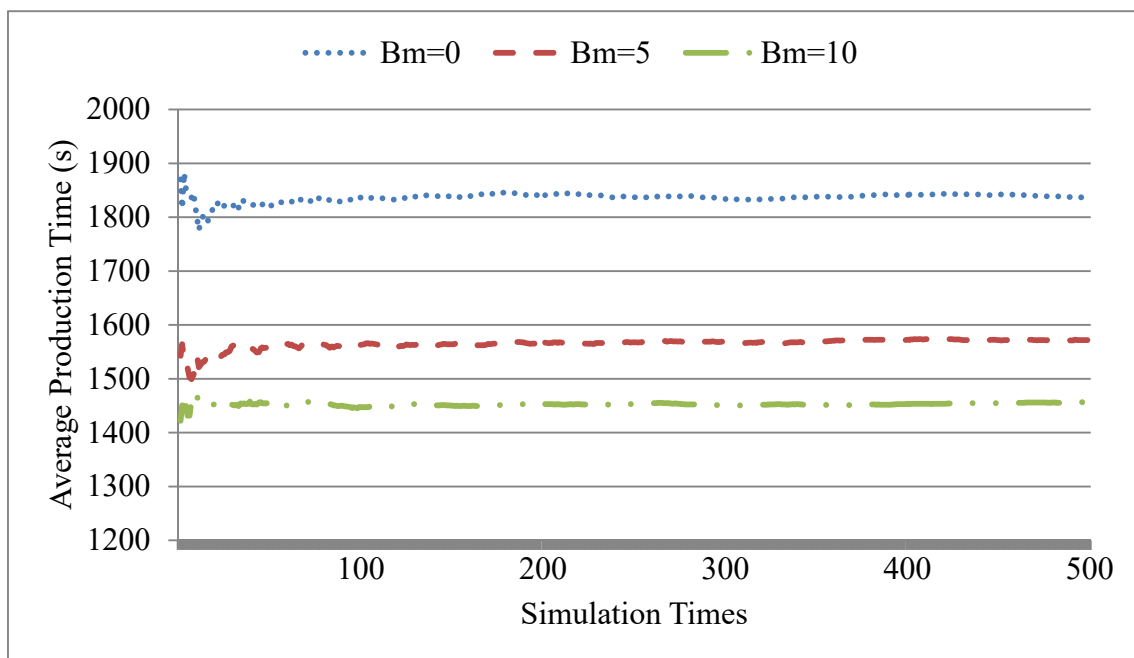
Fig. 3 Convergence of the production time

The production time after processing every product is recorded. **Table 3** gives the regression results. It can be seen from the table that more than 99% of the original uncertainty has been explained by the polynomial. Moreover, the relative errors between the total production times are less than 2% (**Table 4**). Therefore, a second-order polynomial expression represents an excellent fit for approximating the simulation results.

Table 3 Regression results

Configuration	$Q(x_{it})$	Adjusted R-sq	RMSE
B_m=0	$8.35\times10^{-4}\,x^2 + 0.983x + 10$	0.98	6.63
B_m=5	$5.27\times10^{-4}\,x^2 + 1.032\,x + 10$	0.99	4.23
B_m=10	$3.67\times10^{-4}\,x^2 + 1.070\,x + 10$	0.99	3.04

**Table 4** Comparison of the total production time obtained from simulation and regression

Configuration	Simulation result	Regression result	Relative error
$B_m=0$	1837.44	1825.3	1.54%
$B_m=5$	1571.87	1562.9	1.26%
$B_m=10$	1456.15	1445.2	1.05%

Constraint (13) also requires the polynomial expression to fit well the product output in a period. In mass production, the output should be as large as possible without violating the capacity constraint. Assume that the output is larger than 200. Then, the deviation ratio between the simulation and the regression results can be calculated as follows:

$$ratio = abs\left[\frac{\left(\psi(n_2)-\psi(n_1)\right)-\left(Q(n_2)-Q(n_1)\right)}{\left(Q(n_2)-Q(n_1)\right)}\right]\times100\%, \quad n_2-n_1>200 \qquad (14)$$

where n_1 and n_2 are the quantities of produced products.

To estimate the deviation ratio, 1,200 tuples of n_1 and n_2 are randomly generated using the Uniform (1, 1000) function. The majority of ratios are in the interval from -3% to 3%, and the percentage decreases when the system owns a larger buffer (**Fig. 4**). For the system with $B_m = 0$, all ratios are within $\pm3\%$. This ensures the performance of this approximation approach in the integrated planning model.
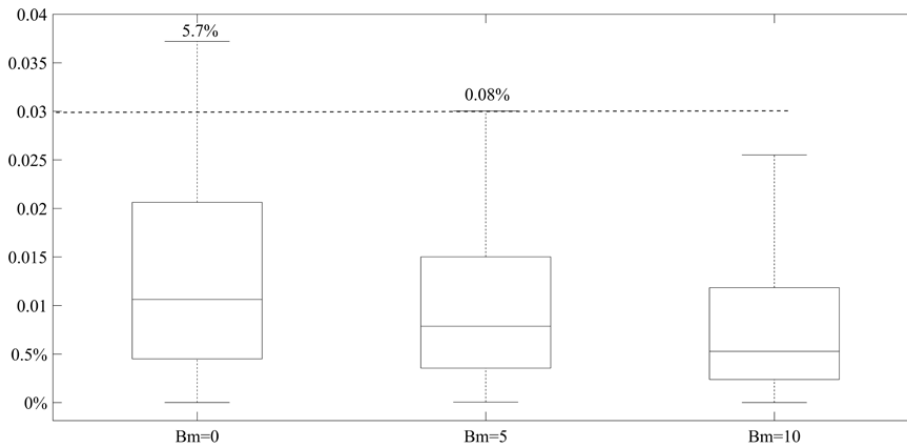
Fig. 4 Absolute values of deviation ratios

4. Case study

Re-consider the unreliable flow line described in Section 3 with the planning horizon being divided into 8 periods and each period having a maximum capacity of 400 time units. Two kinds of products are produced in the flow line and the demand for them are randomly generated between (0, 400) and are listed in **Table 5**. Some parameters (i.e. β_m, η_m, t_m^c) are listed in **Table 2**, and other can be seen in **Table 6**. Then, Lingo 11 is used to minimize the overall cost.

Table 5 Demand for products

Period No.	1	2	3	4	5	6	7	8
Product A	103	62	162	5	17	385	295	89
Product B	191	139	252	394	224	24	171	264

Table 6 Other parameters of the flow line

Parameters	c_{it}	s_{it}	h_{it}	c_s^p	t_s^p	c_m^c	t_m^c
Values	1	600	1	300	40	20	20

4.1   Comparison with the CLSP model

Three levels (i.e. 0, 5, and 10) of the buffer capacity are considered in the CLSP-M models. **Table 7** gives the capacity utilization and costs of the CLSP model and the CLSP-M models. The traditional CLSP model exhibits the lowest value of capacity utilization in all scenarios given in **Table 7**. With the maintenance activities and the multi-stage production characteristics considered in the integrated models, the capacity utilization reaches relatively high percentages, which are over 90%. Some production activities are advanced or postponed in the CLSP-M models, thus the production cost is about 6-12% greater when compared with the CLSP model.

In **Table 7**, the capacity utilization of the CLSP-M model decreases as the buffer capacity increases. It is because the flow line with a larger buffer capacity is always more production efficient and the demand for products is predetermined. Moreover, the more relaxed capacity constraint and higher flexibility of production and maintenance activities result from a lager buffer capacity. Therefore, it can be observed that the overall cost gradually decreases as the buffer capacity increases.

Table 7 Capacity utilization and costs of models

Item/model	CLSP model	CLSP-M model ($B_m = 0$)	CLSP-M model ($B_m = 5$)	CLSP-M model ($B_m = 10$)
Capacity utilization	69.43%	96.42%	92.56%	91.34%
Production cost	11649	13063	12441	12351
Maintenance cost	0	7412.3	7453.6	7477.2
Overall cost	11649	20475.3	19894.6	19828.2

4.2   Validity of the capacity constraint

Three sets of tests were executed, each set for another level of buffer capacity, and each test was simulated 500 times. **Fig. 5** shows the simulation results of the violation of the capacity constraints in the periods. Violations are observed in the periods with tighter production constraints. The violation ratio does not exceed the level of the deviation ratios presented in **Fig. 4**. The violated capacity constraint phenomenon can be decreased by making slight adjustments to the existing decision results.
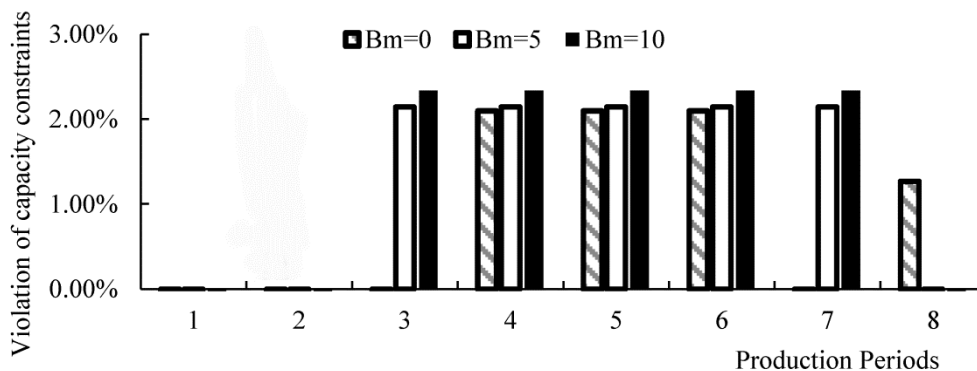
Fig. 5 Capacity constraint verification

5. Conclusion

This paper extends the CLSP from a single-machine/single-stage system to an unreliable flow line. A mathematical model of the CLSP which considers maintenance operations is proposed with the aim of seeking a cost-optimal plan for both production and maintenance. In the model, synchronized preventive maintenance activities are performed to restore unreliable machines, and corrective maintenance is carried out on any machine in which an unplanned failure occurs. A regression-based approximation approach is proposed to obtain an expression of the production time, which is employed in the capacity constraints of the proposed model. Then, the model can be solved by any commercial optimization software. Experiments are conducted to reveal the effectiveness of the approximation approach. Lingo 11 is used to minimize the overall cost of the CLSP-M model. The results indicate that the capacity utilization is greatly improved compared with the CLSP model. Besides, the system configuration has non-negligible effects on the capacity utilization and cost, which should be considered in the integrated planning.

Future work would consider PM on the machine level, which would be more economic in cost. The main problem is to propose an approach to achieve such a production time of the flow line in which machines have different probability distribution. A reactive decision-making model of the CLSP-M considering rescheduling work tasks and PM is also an interesting research trend.

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Wenwen Lin

1. Faculty of Mechanical Engineering & Mechanics, Ningbo University, Ningbo Zhejiang 315211, China

2. Part Rolling Key Laboratory of Zhejiang Province, Ningbo University, Ningbo Zhejiang 315211, China
308 Xiushan Engineering Hall, 818 Fenghua Road, Ningbo, Zhejiang, 315211, China

Yuejun Zhang

Faculty of Mechanical Engineering & Mechanics, Ningbo University, Ningbo Zhejiang 315211, China