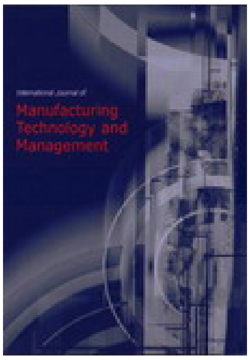

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An intelligent buffer capacity allocation method for flexible production lines based on conjugate Bayes estimation

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Abstract: In order to overcome the problems of low productivity, high vacancy rate and long allocation time in traditional methods, an intelligent buffer capacity allocation method based on conjugate Bayesian estimation is proposed in this paper. Firstly, the basic function of flexible production line is determined, and the relationship between steady performance parameters and buffer capacity is analysed. Secondly, Gershwin decomposition method is used to solve the performance parameters of flexible production line system. Then, the proper conjugate prior information is determined and the process distribution parameters are estimated using conjugate Bayes. Finally, the buffer capacity intelligent allocation value of flexible production line is calculated to realise buffer capacity intelligent allocation of flexible production line. The experimental results show that the proposed method can achieve 97.6% equipment productivity, 2.3% equipment vacancy rate and 6.6s allocation time, and has good buffer capacity allocation effect.

Keywords: conjugate Bayesian estimation; flexible production line; prior information; buffer capacity; intelligent allocation of capacity.

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1 Introduction

At present, a flexible production line has been formed according to the similarities of product specifications, sizes and processes, which plays an increasingly important role in production management. With the integration of global economy and the increase of modern production scale, the competition among enterprises is increasingly intensified (Stockinger et al., 2021; Leng, 2020; Zhu and Xu, 2019). In order to strengthen the competitive advantage of enterprises, it is necessary to strengthen production management and improve production efficiency. How to optimise and rationally allocate existing resources in flexible production lines has become an important task for manufacturing enterprises to reduce costs and improve productivity. Buffers are widely distributed within manufacturing enterprises. Temporary storage of semi-finished products and finished products can reduce the damage and impact of poor conditions of equipment on the performance of the entire system. Because of their temporary storage, impact reduction, balance system and other functions, they cannot be completely eliminated from the actual needs of the enterprise (Abdurashidovich et al., 2020; Liu et al., 2020; Sagron and Pugatch, 2021). Buffer is of great importance to manufacturing enterprises, and the allocation of capacity is a key issue for manufacturing system designers.

At present, scholars in related fields have studied the buffer capacity allocation of production line. Koyuncuoğlu and Demir (2021) proposed a buffer capacity allocation method in production line with adaptive large neighbourhood search. Adaptive large neighbourhood search algorithm is used to solve the problem of throughput buffer allocation in unreliable production line. The relationship model between production line availability and buffer capacity allocation is established by approximation and decomposition method. The removal insertion operator is iteratively trained on the substitution relation model to obtain the optimal solution of buffer capacity allocation. This method can effectively improve the accuracy of buffer capacity allocation, but the allocation takes a long time. Duan et al. (2020) proposed a multi-objective optimisation method for production line buffer capacity allocation based on improved adaptive NSGA-II algorithm. By analysing the polymorphism of production capacity, using the general generation function of extension vector and the improved adaptive NSGA-II algorithm, the mathematical model of buffer capacity optimisation is established and optimised, and the buffer capacity allocation optimisation of production line is realised by information entropy method. This method can improve the buffer allocation effect of the production line, but the buffer allocation effect is poor.

To solve the above problems, this paper presents an intelligent buffer capacity allocation method for flexible production lines based on conjugate Bayes estimation. The specific technical route is as follows:

Step 1 Basic function description of flexible production line. The basic function of flexible production line is determined, and the relationship between steady performance parameters and buffer capacity of flexible production line is analysed.

Step 2 The basic function of flexible production line can be solved. The Gershwin decomposition method is used to solve the performance parameters of flexible production line system.

Step 3 Flexible production line buffer capacity intelligent allocation. Based on the conjugate apriori information, the process distribution parameters are estimated by using conjugate Bayes, and the buffer capacity allocation value is calculated.

Step 4 Verifying the effect of buffer capacity intelligent allocation of flexible production line by buffer capacity allocation time, equipment productivity and equipment vacancy rate.

2 Design of buffer capacity intelligent allocation method for flexible production line based on conjugate Bayesian estimation

In this paper, the buffer capacity allocation problem of flexible production line is solved with the aim of maximising the productivity of flexible production line.

2.1 Building basic functions of flexible production line

In order to realise intelligent allocation of buffer capacity in flexible production line, the basic function of flexible production line is described firstly (Shaaban and Romero-Silva, 2021). In the intelligent allocation of buffer capacity, flexible production line is the research foundation of large-scale manufacturing system (Ferreira et al., 2020; He et al., 2019; Wang, 2020), which consists of R equipment (U_1, U_2, …, U_R) and $R - 1$ buffer (I_1, I_2, …, I_{R-1}). In the flexible production line system operation process, raw materials from the first equipment U_1 into flexible production line for processing, and then into the buffer I_1, and then through the order of various flexible production line equipment and buffer, and finally from the equipment U_R to complete processing and exit flexible production line system.

Suppose the buffer capacity of each buffer is E_i, $i \in \{1, 2, \dots, R - 1\}$, the processing rate of each equipment of flexible production line is O_i, $i \in \{1, 2, \dots, R\}$, the processing time is P_i, $i \in \{1, 2, \dots, R\}$, the failure rate is Y_i, $i \in \{1, 2, \dots, R\}$, and the maintenance rate is A_i, $i \in \{1, 2, \dots, R\}$. The relationship between the maintenance rate and the failure rate is as follows:

$$S_i = \frac{Y_i}{A_i}, \alpha_i = \frac{A_i}{A_i + Y_i} \tag{1}$$

In formula (1), α_i is the independent production efficiency of flexible production line equipment U_R. Based on continuous function, the performance parameters of equipment in flexible production line are defined. Assuming that the efficiency of the equipment U_R of the flexible production line is β_i, the productivity of the equipment U_R is γ_i, the vacancy rate of the equipment U_R is δ_i, the hunger rate of the equipment U_R is ε_i, the blocking rate of the equipment U_R is ϵ_i, and the probability of the equipment U_R is θ_i, the performance parameters have the following correlations:

$$\delta_i + \beta_i + \theta_i = 1 \tag{2}$$

$$Y_i \cdot \beta_i = A_i \cdot \theta_i \tag{3}$$

From formulas (1) and (3):

$$\beta_i = \alpha_i \left(1 - \varepsilon_i - \epsilon_i\right) \tag{4}$$

Flexible production line equipment productivity and efficiency meet:

$$\gamma_i = O_i \cdot \beta_i \tag{5}$$

The average surplus level of buffer zone I_{R-1} is defined as F_i, and the steady-state production capacity of the entire flexible production line system is defined as G_i.

$$G_i = \gamma_i, F_i = \sum_{i=1} G_i \tag{6}$$

Through the above steps, the relationship between equipment and buffer capacity of flexible production line is analysed according to the steady-state performance parameters of basic function.

2.2 Solution of basic function parameters of flexible production line

On the basis of describing the basic function of flexible production line, Gershwin decomposition method is used to solve the performance parameters of flexible production line. Its main ideas are as follows:

The H of R equipment is decomposed into $H(i)$ of $R - 1$ equipment flexible production line. Each flexible production line $H(i)$ consists of upstream equipment $U_u(i)$ and downstream equipment $U_d(i)$, intermediate buffer $I(i)$. The decomposition method is to determine the unknown parameters of the flexible production line $H(i)$ for each device, so that the operation characteristics of buffer $I(i)$ are similar to those of buffer I_{R-1}. In particular, the productivity of the flexible production line $H(i)$ equals the productivity of the equipment U_R in the original flexible production line H:

$$\gamma(i) = \gamma_{i+1} \tag{7}$$

The $U_u(i)$ blocking rate of upstream equipment in flexible production line $H(i)$ is equal to the blocking rate of equipment U_R in the original flexible production line H:

$$\epsilon(i) = \epsilon_{i+1} \tag{8}$$

The hunger rate of $U_d(i)$ in the downstream equipment of flexible production line $H(i)$ is equal to the hunger rate of U_R in the original flexible production line H, namely:

$$\varepsilon(i) = \varepsilon_{i+1} \tag{9}$$

From formulas (5) and (7):

$$\beta(i) = \beta_{i+1} \tag{10}$$

Similarly, according to the above process, the parameters of $H(i + 1)$ of the flexible production line are substituted, and the basic function performance parameters of the flexible production line can be obtained.

2.3 Intelligent allocation of buffer capacity in flexible production line

Conjugate Bayesian estimation is also a common Bayesian estimation method. Conjugate Bayesian estimation selects conjugate prior information other than uninformed prior information (Xu, 2020; Nishida, 2019; Perišić e al., 2021).

Based on conjugate Bayesian estimation, this paper realises intelligent buffer capacity allocation in flexible production lines. First, determine the appropriate conjugate priori information. In order to guarantee the credibility of conjugate prior information, we regard conjugate prior information as a prior distribution in the same parameter family. Use Bartlett test (Odoi et al., 2019) to determine whether the overall changes between the previous μ batch buffer and the current $\mu + 1$ batch buffer are different. The initial assumption of the Bartlett test is that the overall variance ρ is the same across buffer regions.

In the $\mu + 1$ batch buffer of E_i buffer capacity of flexible production line, the estimation of ρ is replaced by buffer variance. The statistical quantities of Bartlett test are as follows:

$$\chi = \frac{(E-\mu-1)\ln(\kappa) - \sum_{i=1}^{\mu+1}(E_i - 1)\ln\lambda}{1 + 3\mu\sum_{i=1}^{\mu+1}\left(\frac{1}{E_i - 1}\right)} \tag{11}$$

In formula (11), E refers to the total buffer capacity of the flexible production line, κ refers to the buffer variance, and λ refers to the average buffer variance. According to the characteristics of conjugate Bayesian estimation, the global average requirements are equal in a priori and a posteriori distribution. One-way ANOVA is mainly used to determine the average error of each buffer area of flexible production line. That is to say, using the F test, the overall average equality of the $v + 1$ batch buffer for the initial assumption is true.

In the $v + 1$ batch buffer of E_i buffer capacity of the flexible production line, the estimated value of ϱ is replaced by the buffer mean ϖ_i, and the statistics of the F test are expressed as follows:

$$\varphi = \frac{\sum_{i=1}^{v+1}(\varpi_i - \varpi)\big/ v}{\sum_{i=1}^{v+1} E_i(E - v - 1)} \tag{12}$$

In formula (12), ϖ refers to the average of the total buffer capacity.

On this basis, the process distribution parameters are estimated by conjugate Bayes. For flexible production lines, the total variance η_t of the current buffer needs to be known when estimating the buffer capacity allocation within the current batch.

The results of Bayesian statistics show that the average mean ς of the whole process must be assumed to be invariant and the η_t to be inverse gamma distribution must be assumed for Bayesian estimation of the overall variance η_t of the uncertain current buffer. The probability density function of η_t is:

$$f(\eta z, x) = \exp\left(\frac{-x}{z}\right)\varsigma \tag{13}$$

In formula (13), z is the shape parameter and x is the scale parameter. The distribution parameters are obtained from prior information and calculated as follows:

$$L\{\eta_t | \eta_1, \eta_2, ..., \eta_t\} = \frac{x^2}{(z-1)^2(z-2)} \tag{14}$$

The current buffer is obtained, and the overall variance η_t of the buffer follows an anti-Gamma distribution. It can be seen from the conjugate Bayesian properties that the posterior distribution of η_t also follows the anti-Gamma distribution. Therefore, the Bayesian estimation of K is changed to η_t, and the results are as follows:

$$K = \frac{x + \frac{1}{2}\sum_{i=1}^{n}(\varpi_i - \varsigma)^2}{z - 2 - 1} \tag{15}$$

Assuming $\varsigma \sim E(\xi, \psi^2)$, the value of the distribution parameter ξ, ψ^2 can be obtained in advance, that is:

$$\xi = \frac{1}{z}\sum_{i=1}^{z}\varpi_i, \psi^2 = \frac{1}{z-1}\sum_{i=1}^{z}(\varpi_i - \xi)^2 \tag{16}$$

Therefore, the posterior distribution parameters are calculated as follows:

$$\Phi = \frac{K\psi^2}{K + x\psi^2} \tag{17}$$

For the average ς for the whole process, its Bayesian estimate is as follows:

$$\Omega = \frac{\psi^2}{\eta_t / \varpi_i}\xi \tag{18}$$

Finally, the buffer capacity intelligent allocation value is calculated. Using K and Ω instead of η_t and ς in the formula, the intelligent buffer capacity allocation of flexible production line is calculated with unknown ρ and ς. The Bayesian estimates are as follows:

$$\begin{cases} K = \dfrac{x + \frac{1}{2}\sum_{i=1}^{n}(\varpi_i - \Omega)^2}{z - 2 - 1} \\ \Omega = \dfrac{\psi^2}{K/\varpi_i}\xi \end{cases} \tag{19}$$

The value of K and Ω is calculated by simultaneous equations, and then the intelligent buffer allocation value of flexible production line is obtained by conjugate Bayesian method. This allocation value is determined by prior information and K and Ω of the current flexible production line buffer capacity. With the change of buffer capacity of flexible production line, the allocation value will be automatically adjusted according to the change of buffer capacity and prior information. Through the above process, the buffer capacity intelligent allocation of flexible production line based on conjugate Bayes estimation is realised.

3 Experimental analysis

3.1 Experimental scheme

In order to verify the effectiveness of the buffer capacity allocation method based on conjugate Bayesian estimation in flexible production line, a flexible production line is modelled by using Flexsim. The emulator is a Windows 8.1 64-bit system with a

2.40 GHz Core 5-4258U dual-core processor. In this section, the dissimilar hybrid parallel production line composed of six devices and four buffers is taken as the experimental object for example analysis, and its performance analysis and capacity allocation are carried out by using conjugate Bayesian estimation. The actual operation process of the software module is shown by an example. The equipment parameters of the production line are shown in Table 1.

Table 1 Equipment parameters of dissimilar hybrid parallel production line L16

	M_1	M_2	$M_{1,1}$	$M_{1,2}$	$M_{2,1}$	$M_{2,2}$
T_i	0.8	1.1	0.9	0.7	1.2	1.0
p_i	0.05	0.06	0.04	0.05	0.03	0.07
r_i	0.07	0.06	0.05	0.07	0.04	0.09

3.2 Experimental indicators

Based on the experimental scheme set above, the equipment vacancy rate, equipment productivity and capacity allocation time are analysed as performance indicators.

1 Equipment vacancy rate: the calculation formula of equipment vacancy rate is as follows:

$$\Lambda = \frac{S_Y}{Q_Y} \times 100\% \tag{20}$$

In formula (20), the number of unused flexible production line equipment is expressed as the number of flexible production line equipment.

2 Equipment productivity: the calculation formula of equipment productivity is as follows.

The ratio of output γ_{of} such as productivity $\gamma(i)$ of flexible equipment production line to input γ_{in}:

$$\gamma(i) = \frac{\gamma_{of}}{\gamma_{in}} \times 100\% \tag{21}$$

The higher the productivity of flexible production line equipment, the better the distribution effect of this method. On the contrary, the lower the productivity of flexible production line equipment, the worse the distribution effect of this method.

3 Capacity allocation time: refers to the time difference between the start time of capacity allocation time and the end time of capacity allocation of flexible production line equipment. Capacity allocation time is an important index to measure the capacity allocation efficiency of flexible production line equipment. The longer the capacity allocation time, the lower the capacity allocation efficiency of production line equipment. On the contrary, the shorter the capacity allocation time, the lower the capacity allocation efficiency of production line equipment.

4 Comparison method: Koyuncuoğlu and Demir (2021) method, Duan et al. (2020) method and the proposed method are used to verify the effectiveness of the proposed method.

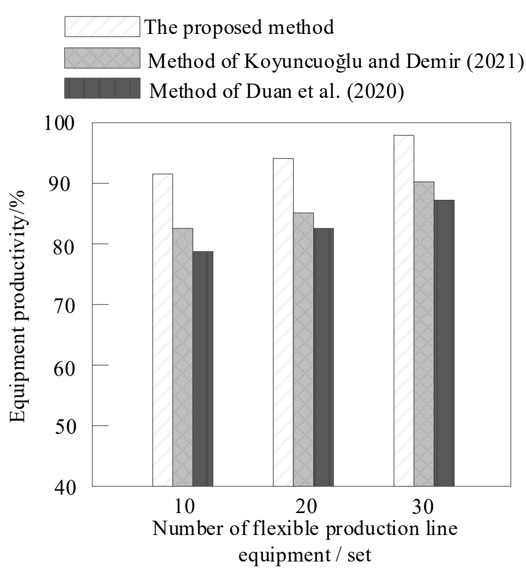
3.3 Analysis of buffer capacity allocation effect of flexible production line

3.3.1 Equipment productivity of flexible production lines

In order to verify the buffer capacity allocation effect of flexible production line, the equipment productivity is used as an evaluation index. The higher the equipment productivity is, the better the buffer capacity allocation is. By using the methods of Koyuncuoğlu and Demir (2021), Duan et al. (2020) and the proposed method, the comparative results of the equipment productivity of flexible production lines with different methods are shown in Figure 1.

Analysis of Figure 1 shows that with the increase of the number of flexible production line equipment, the different methods of flexible production line equipment productivity increases. When the number of flexible production line equipment reaches 30, the equipment productivity of flexible production line with Koyuncuoğlu and Demir (2021) method is 90%, and that with Duan et al. (2020) method is 87.5%. The equipment productivity of flexible production line is up to 97.6%. Thus, the proposed flexible production line has higher equipment productivity, which indicates that the proposed method has good buffer capacity allocation effect.

Figure 1 Comparative results of equipment productivity of flexible production lines with different methods



3.3.2 Buffer capacity allocation accuracy of flexible production line

On this basis, the buffer capacity allocation accuracy of flexible production line is verified, and the equipment vacancy rate is used as an evaluation index. The lower the equipment vacancy rate is, the higher the accuracy of buffer allocation is. Using the methods of Koyuncuoğlu and Demir (2021), Duan et al. (2020) and the proposed method to compare, get different methods of flexible production line equipment vacancy rate comparison results as shown in Figure 2.

Figure 2 Comparison of equipment vacancy rate of flexible production lines with different methods

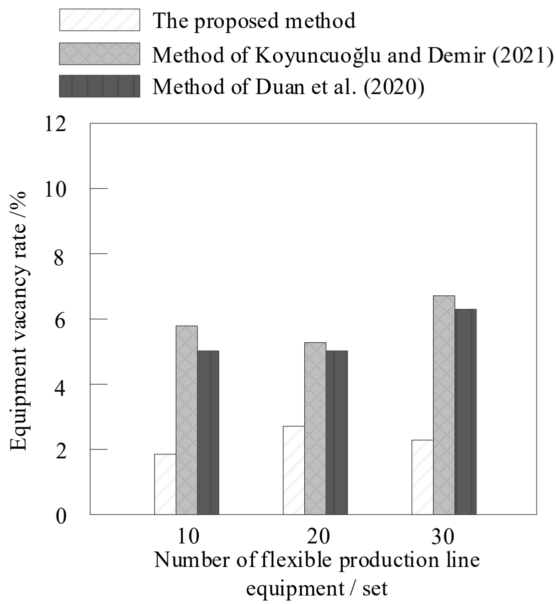


Figure 2 shows that when the number of flexible production line equipment reaches 30, the average equipment vacancy rate of the flexible production line using Koyuncuoğlu and Demir (2021) method is 5.97% and that of the flexible production line using Duan et al. (2020) method is 5.4%. The average equipment vacancy rate of the proposed method is only 2.3%. Thus, the proposed method of flexible production line equipment vacancy rate is lower, indicating that the proposed method of flexible production line buffer capacity allocation accuracy is higher.

3.3.3 Buffer capacity allocation time of flexible production lines

The buffer capacity of flexible production line is set to 300, and the buffer capacity allocation time of flexible production line is further verified. The buffer capacity allocation time of flexible production line with different methods is compared with the methods of Koyuncuoğlu and Demir (2021) and Duan et al. (2020), and the results are shown in Table 2.

Analysis Table 2 shows that buffer allocation time of flexible production line increases with the increase of buffer capacity. When buffer capacity of flexible production line is 300, buffer allocation time of flexible production line is 11.6 s by Koyuncuoğlu and Demir (2021) method, 14.2 s by Duan et al. (2020) method and 6.6 s by proposed method. Therefore, the buffer capacity allocation time of flexible production line is shorter.

Table 2 Buffer allocation time comparison results of flexible production lines with different methods

Flexible line buffer capacity	*Proposed method/s*	*Koyuncuoğlu and Demir (2021) method/s*	*Duan et al. (2020) method/s*
100	2.8	5.6	8.9
200	4.9	8.4	11.6
300	6.6	11.6	14.2

4 Conclusions

This paper presents an intelligent buffer capacity allocation method for flexible production line based on conjugate Bayesian estimation. By describing the basic function of flexible production line, the steady-state performance parameters are obtained and solved. On the basis of determining the conjugate prior information, the conjugate Bayesian method is used to estimate the process distribution parameters, calculate the intelligent allocation value of buffer capacity of flexible production line, and realise the intelligent allocation of buffer capacity of flexible production line. The following conclusions are drawn through experiments:

1 The equipment productivity of flexible production line is up to 97.6%, which has good buffer capacity allocation effect.

2 The average equipment vacancy rate of the flexible production line is only 2.3%, and the buffer capacity allocation accuracy of the flexible production line is high.

3 The buffer capacity allocation time of flexible production line is only 6.6s, which can effectively shorten the buffer capacity allocation time of flexible production line.

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