Taylor & Francis
Taylor & Francis Group

International Journal of Production Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

Designing a resilient production system with reconfigurable machines and movable buffers

Tong Qin, Ruxu Du, Andrew Kusiak, Hui Tao & Yong Zhong

INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH
2022, VOL. 60, NO. 17, 5277–5292
https://doi.org/10.1080/00207543.2021.1953715

Designing a resilient production system with reconfigurable machines and movable buffers

Tong Qin[a], Ruxu Du[a], Andrew Kusiak [b], Hui Tao[a,c] and Yong Zhong [a]

[a]S. M. Wu School of Intelligent Engineering, South China University of Technology, Guangzhou, People's Republic of China; [b]Department of Industrial and Systems Engineering, University of Iowa, Iowa City, IA, USA; [c]National and Local Joint Engineering Research Center for Industrial Friction and Lubrication Technology, Guangzhou, People's Republic of China

ABSTRACT

The resilience of a production system is determined by its capability to respond to internal breakdowns and/or external disruptions and recover. In conventional production systems, internal disruptions such as machine breakdown are handled by parallel stations and storage buffers, which come at a cost. In this paper, we propose to use reconfigurable machines (RMs) and movable buffers (MBs) to increase the resilience of a production system. The production system is modelled using a modified Markov chain model. To reduce the computational effort, an iterative method is adopted for the production lines that have many RMs and MBs. The resilience of the production system is evaluated by a combination of production loss, steady production rate with threshold, work-in-process in Idle-area of MBs, process time of work-in-process in Idle-area of MB with threshold, and investment return. Two production systems are analysed, one with 3 operations and the other with 10 operations. The computer simulation results indicate that the resilience of a production system can be improved by more than 9% by RMs and MBs. Finally, a set of guidelines for design production systems with RMs and MBs are also given.

ARTICLE HISTORY
Received 10 March 2021
Accepted 2 July 2021

KEYWORDS
Resilience management; design of production systems; reconfigurable manufacturing systems; movable buffer; Markov chain

Nomenclature

$\boldsymbol{A^j}(n)$	state probability transition matrix of jth 2-stages-1-buffer module at cycle n
C_P	cost per part
C_O	cost per minute of overtime
CA_j	buffer capacity $T_j, j = 1, 2, \cdots, N-1$
CA_{MB}	capacity of the Idle-area of movable buffers
FC	fixed cost of building and running the production system
IR	return on investment
M_i	number of stations at stage i, where $i = 1, 2, \cdots, N$
N	number of production stages
$O_j(n)$	utilisation of buffer T_j at the end of cycle n
OP_m	number of operations that reconfigurable machines can process, $m \in N^+$
p_s	Bernoulli reliability of switch of reconfigurable machine in one cycle
p_{MB}	probability of each successful move to the specified location
PL	production losses caused by machine breakdowns
$PR(n)$	production at cycle n
SPR_δ	the breakdown-free steady production rate with threshold δ
SO_i	number of working machines that at stage i of production cycle n (only affected by the of its own machine Bernoulli reliability and regardless of the utilisation of the front and rear buffers)
$S0_i^P$	probability vector of SO_i
$S_i(n)$	the number of products processed by stage i at cycle n (affected by Both Bernoulli reliability and the utilisation of front and rear buffers)
$\boldsymbol{S_i^P}(n)$	probability vector of $S_i(n)$
T_j	buffer $j = 1, 2, \cdots, N-1$
t_r	the time when the $PR(n)$ is restored to the steady state after a breakdown
WIPM	work-in-process in movable buffers
$\mathrm{WIP}TM_\gamma$	process time of work-in-process in movable buffers with threshold γ
$\boldsymbol{x_j}$	state vector of buffer j
$\boldsymbol{x_{MBj}}$	state vector that replaces the Idle-area of the movable buffers of the buffer T_j.
$\boldsymbol{x_j^P}(n)$	probability vector of $\boldsymbol{x_j}$ at the end of cycle n

CONTACT Yong Zhong zhongyong@scut.edu.cn

$x^P_{MBj}(n)$	probability vector of x_{MBj} at the end of cycle n
ΔT	production cycle
Y	yield without any breakdown.

1. Introduction

With ever increased global competition and manufacturing uncertainty, manufacturing companies need to re-examine their operations from the resilient perspective (Kusiak 2020). Many studies on resilience in different domains have been published, e.g. ecological resilience (Müller et al. 2016), economic resilience (Simmie and Martin 2010), urban resilience (Ouyang, Dueñas-Osorio, and Min 2012), transportation system resilience (Mattsson and Jenelius 2015), distribution network resilience (Gao et al. 2015), food supply resilience (Tendall et al. 2015), psychological resilience (Xi, Zuo, and Wu 2012), and manufacturing resilience (Dinh et al. 2012; Kusiak 2019). Production resilience examines possible breakdowns and recovery in global and local contexts. It has been reported that a seemingly small number of events may result in significant damage to the industry worldwide (Sawik 2018). For example, the 2016 earthquake in Taiwan shut down many semiconductor factories, and directly affected Japan, Korean, China, and the USA (Wan 2016). In 2011, a flood in Thailand caused a sharp drop in global hard disk shipments with soaring prices (Coughlin 2011). Some kinds of breakdowns are uncontrollable and unpredictable, it is generally agreed that breakdowns should be managed rather than simply suppressed (Hollnagel 2012). In other words, resilience should emphasise the system ability to withstand, absorb, and recover from internal breakdowns or external disturbances (Alliance 2021). Typically, the resilience of a production system depends on many factors including product design (Haug 2018), material/component supply (Cavalcante et al. 2019), production system setup (Jin and Xi 2016), production system control (Zou et al. 2019), as well as sales and service network (Kakadia and Ramirez-Marquez 2020). This paper focuses on the design of production systems, particularly, production lines.

Parallel stations or lines and large-capacity storage buffers are used to improve resilience of a production system (Dinh et al. 2012), but the shortcomings of the two methods include higher costs and more space. With the advancement of computer and robotic technologies, it is possible to use other strategies to improve resilience of a production system, such as Reconfigurable Machines (RM) and Movable Buffers (MB). RM is the machine that can change the machine structure or parameters to achieve more functions (Koren et al. 2003). MB is a buffer with both moving and storing functions (Chang, Fu, and Hu 2006). The Numerical Control multi-function RM was first introduced in the study by Koren et al. (2003). Bi et al. (2007) summarised the development of RM from 1990 to 2007 and discussed the limitations. In the past decade, the research kept moving forward and several applications were developed (Katz 2007; Gadalla and Xue 2018; Tian, Liang, and Pan 2007). Zhang and van Luttervelt (2011); Gu et al. (2015) had shown that the RM can improve the resilience of the production system because it can maintain the production process by reconfiguring to achieve the function of the nearest stations in the event of a failure, although productivity may not be full. However, they only considered making improvements to the machines instead of the buffer, such as using MB. The buffers can increase the resilience of the production systems (Dinh et al. 2012). By using a robot for part handling and an AGV for part transportation, one can make an MB. This concept has appeared in recent years. For example, D'Souza, Costa, and Pires (2020) proposed to add a collaborative robot to an industrial AGV. Chang, Fu, and Hu (2006) gave an innovative mobile automated storage/retrieval system by using an integrated multi-level conveying device for automated picking operation. Such an MB can replace a number of buffers effectively. Nonetheless, they did not discuss the impact of using MB on resilience in production systems.

There are several different methods for modelling production systems, of which the Markov chain is a generally applicable method (Meerkov and Zhang 2008). Unfortunately, it suffers from a dimension size problem. Exponential growth in dimensionality also increases computational complexity. In other words, dimension reduction is necessary. Gu et al. (2015); Zhang et al. (2013) proposed their algorithms to approximate dynamic performance. In Zhang et al. (2013), the production system is split into stages and each stage contains only one machine but there is no RM and MB. In Gu et al. (2015), the same split approximation method is used to model production lines with RM added but no MB. Therefore, their methods are not applicable to our design. This paper proposes a way to achieve dimension reduction for modelling the production process of line with RM and MB. The method applies to any number of buffers and has been shown to be highly accurate. For evaluating the resilience of production systems, Zhang and van Luttervelt (2011); Gu et al. (2015) had proposed that the resilience of production systems could be measured using several indices, such as Production Loss (PL), Total Underproduction Time (TUT), and Throughput Settling Time (TST). However, they did not take into account MB. In fact, while a multi-functional RM can be considered as a device like a parallel station that eases the spatial constraints, MB can be considered as a device similar to a conventional storage buffer that eases the time constraints. This combination will ease the impact of production breakdown and, hence, improve the resilience of a production system. Therefore, this paper proposes other resilience indices applicable to MB including Work-In-Process (WIP), Work-In-Process in Idle-area of Movable Buffer (WIPM), Process Time of Work-In-Process in Idle-area of Movable Buffer with Threshold γ (WIPTM$_\gamma$), and Investment Return (IR).

In this paper, we present a novel study on the design of resilient production systems using both RM and MB. Firstly, a general MB conceptual structure is given. Secondly, an iterative model is established for the production process with RM and MB production lines, and new indices are proposed. Finally, two examples are given to show that both MB and RM can improve the resilience. In summary, the effects of using MB or both RM and MB on the resilience of production systems have not been discussed before. This paper proposed that MB can improve system resilience and using both RM and MB is more efficient than using either of them.

The rest of the paper is organised as follows. An iterative algorithm rather than a traditional Markov chain model for modelling the production process of line with RM and MB is formulated in Section 2. Several resilient indices are also discussed. Section 3 shows two simulation examples, both of them use the iterative algorithm. Finally, in Section 4, some guidelines for designing resilient manufacturing systems using RM and MB are summarised and future works are also described.

2. The modelling of a production system

2.1. The layout and the assumptions

Consider a production system with N stages, each having $M_i (i = 1, 2, \cdots, N)$ stations and every station is occupied by one or several machines as shown in

Figure 1. Every machine can work on one or more operations. Between each pair of successive stages, there may be a buffer $T_j (j = 1, 2, \cdots, N-1)$ and its capacity is CA_j (i.e. it is capable of holding CA_j parts). To analyse its behaviour, following assumptions are made:

(1) In a production cycle, each machine follows the Bernoulli reliability model with probability is p (i.e. its reliability is p).
(2) The machines in the first stage will not be starved. However, machines at stage $i (2 \le i \le N)$ will be starved if they are up but the buffer T_{i-1} is empty or the number of working machines at stage i is greater than the buffer T_{i-1} occupied capacity at the beginning of a cycle.

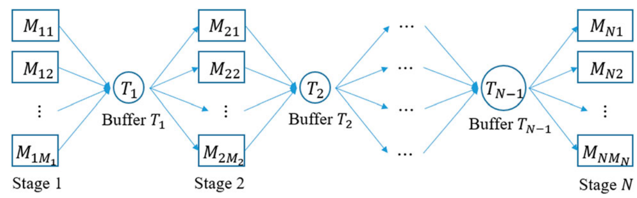


Figure 1. Illustration of an N stage production system.

(3) The machines in the last stage will not be blocked. Nonetheless machines at stage $i (1 \le i \le N-1)$ will be blocked if they are up running but the successor buffer T_i is full or the number of working machines at stage i is greater than the remaining capacity of the buffer T_i at the beginning of a cycle.
(4) The breakdown of a machine (or operation in the machine) occurs only at the beginning of a production cycle.
(5) Breakdowns occur when the production system is running in steady state (i.e. the beginning and the ending of the production run, no breakdowns may incur).
(6) Only a single type of product is produced and it needs to go through the entire the production system stage by stage. The transfer time between stages and buffers are neglectable.
(7) The WIPs produced at stage $i (1 \le i \le N-1)$ at the end of each production cycle are placed in the buffer T_j or Area-j of MB and not counted in the yield (Y) but those in Idle-area of MB (WIPM) are.

Now, consider the production system with RM and MB. When a breakdown incurs, RM can be reconfigured to prevent the entire production system being shut down, though, the production rate (PR) will still decline. The use of RM may result in structural changes of the production system, because an RM in a given stage can be used for its predecessor stage or successor stage. In this case, the number of machines in a stage and even the number of stages may alter. Accordingly, both the state vector and the transition probability matrix need to be changed. A typical RM can be modelled as shown in Figure 2. It can handle several operations, $OP_1, OP_2, \cdots, OP_m, m \in N^+$. Each OP can replace the function of stage $i, i \in \{1, 2, \cdots, N\}$ in the production line. Within a RM, there are connecting channels among the operations. Additionally, a switch is used to select the concrete operation. Similar to the machines, RM follows Bernoulli reliability with probability p_s in a cycle.

MB can be considered as an AGV with a robot loading arm as shown in Figure 3. It would have several storage areas, Idle-Area, Area-1, Area-2, etc., to store parts for different stages. Specifically, Area-1, Area-2, ... are

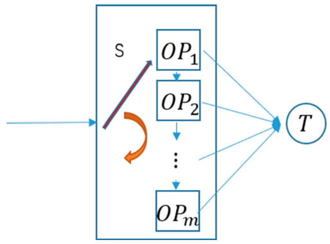


Figure 2. The model of an RM.

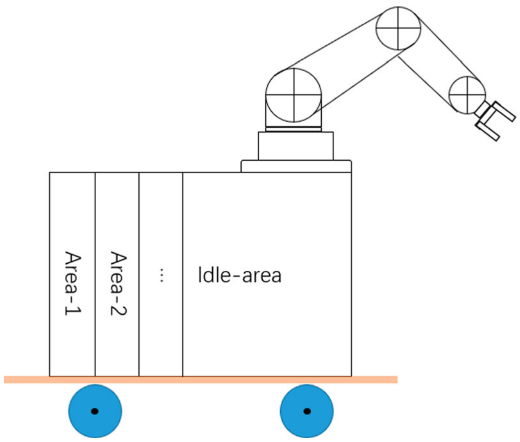


Figure 3. The model of an MB.

the same as buffers T_1, T_2, ... , while Idle-area is used to replace T_{i-1} when a machine in stage i breaks down. When a station in breaksdown or blocks, MB moves to its predecessor station, collects the parts, and stores them for later usage. MB should have sufficient time to move around different stages. Therefore, it typically covers no more than four stages. Moreover, its cost would be lower than three fixed buffers as only one robot is used instead of three. Another advantage of MB is that it could reduce the size of a production system by eliminating the buffers. The capacity of an MB is determined by its reliability p_{MB} (the probability of each successful move to the specified location and there could be multiple movements in a cycle.), capacity of storage area (i.e. the size of Idle-Area, Area 1, Area 2, ...) as well as its moving speed. For simplicity, in the following discussions, it is assumed that MB has limited storage area but infinite moving speed.

2.2. Model building and dimension reduction

First, the production cycle time needs to be determined. In general, the production cycle time is taken as the maximum among the cycle times of all the stages. This may result in long idleness for fast machines. Hence, considering each stage running on its own cycle time, the cycle of the production system, $\boldsymbol{\Delta} T$, is as follows:

$$\Delta T = \text{The GCD of the cycle times in all stages} \quad (1)$$

where GCD is the Greatest Common Divisor. The use of GCD has little impact in the analysis of steady-state performance of the system. But it affects the dynamic performance in the event of machine (or operation) breakdown or production fluctuation. Moreover, it would increase the complexity of the model because the cycle time in each stage could be different. As an example, in a two-stage serial production line, Stage 1 has the cycle time 2 and Stage 2 has the cycle times 3, then, $\Delta T = 1$. The Stage 2 will not complete its operation when n is divisible by 2 but not by 3, while Stage 1 will not complete its operation when n is divisible by 3 but not by 2, where $n \in N^+$.

The dimension of the model is dependent on the number of buffers and the capacity of each buffer. With the increase of the number of buffers and their capacities, the dimension will quickly become too large. For the example, suppose there are three buffers and each buffer can store nine parts, then the dimension of the model will be $(9 + 1)^5 = 100,000$. Consequently, the state probability transition matrix will become a $100,000 \times 100,000$ matrix. Such a dimension will cause various problems such as computation time and numerical error. Hence, reducing the dimension is desirable.

For the production system during breakdown-free periods, we developed another dimension reduction algorithm based on iterative reduction (Gu et al. 2015). As shown in Figure 4, the idea is to decompose the production line into a number of two-stage stations. The right hand side except stage N and the left hand side except stage 1 of the two-stage stations.

To form the iteratively reduced dimension model, we define:

$O_j(n)$ as the utilization of buffer $T_j (j = 1, 2, \cdots, N-1)$ at the end of cycle n;

$\boldsymbol{x_j} = [01 \cdots CA_j]^T$ the state vector of buffer j, and $\boldsymbol{x_j^P}(n)$ the probability vector of $\boldsymbol{x_j}$, i.e. $\boldsymbol{x_j^P}(n) = [P\{O_j(n) = 0\}P\{O_j(n) = 1\} \cdots P\{O_j(n) = C_j\}]^T = [x^P_{j,0}(n) \quad x^P_{j,1}(n) \quad \cdots \quad x^P_{j,CA_j}(n)]^T$.

The iterative reduced dimension model for the jth 2-stage-1-buffer module is as follows:

$$\boldsymbol{x_j^P}(n) = \boldsymbol{A^j}(n)\boldsymbol{x_j^P}(n-1) \quad (2)$$

where $\boldsymbol{A^j}(n)$ is the state probability transition matrix of the jth 2-stage-1-buffer module at cycle n. It has the structure below:

$$\boldsymbol{A^j}(n) = \begin{bmatrix} A^j_{00}(n) & \cdots & A^j_{1CA_j}(n) \\ \vdots & \ddots & \vdots \\ A^j_{CA_j1}(n) & \cdots & A^j_{CA_jCA_j}(n) \end{bmatrix}$$

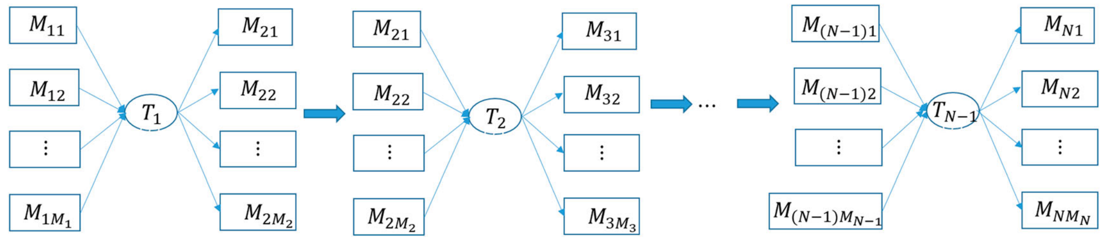


Figure 4. Decomposed production line structure.

Next, define $SO_i \in \{0, 1, \cdots, M_i\}$ as the number of parts processed in stage $i, i = 1, 2, \cdots, N$, in a cycle. Note that it is only affected by its Bernoulli reliability regardless of the utilisation of its predecessor buffer and the successor buffer. Define $\boldsymbol{SO}_i^P$ as the probability vector of SO_i:

$$\boldsymbol{SO}_i^P = \left[P\{SO_i = 0\} \quad P\{SO_i{=}1\} \quad \cdots \quad P\{SO_i{=}M_i\}\right]^T$$
$$= \left[SO_{i,0}^P \quad SO_{i,1}^P \quad \cdots \quad SO_{i,M_i}^P\right]^T.$$

Then, define $S_i(n) \in \{0, 1, \cdots, M_i\}$ as the number of parts processed by stage $i, i = 1, 2, \cdots, N$ at cycle n. Similarly, it is only affected by its Bernoulli reliability regardless of the utilisation of its predecessor buffer and the successor buffer. Define $\boldsymbol{S}_i^P(n)$ as the probability vector of $S_i(n)$:

$$\boldsymbol{S}_i^P(n) = [P\{S_i(n) = 0\} \quad P\{S_i(n) = 1\} \quad \cdots \quad P\{S_i(n) = M_i\}]^T$$
$$= \left[S_{i,0}^P(n) \quad S_{i,1}^P(n) \quad \cdots \quad S_{i,M_i}^P(n)\right]^T.$$

Then, each element in the transition matrix $\boldsymbol{A}^j(n)$ can be calculated as follows:

$$A^j_{O_j(n)O_j(n-1)}(n) = \begin{cases} \sum_j S^P_{j,S_j(n)}(n) S^{P,r}_{j+1,S_{j+1}(n)}(n), \\ \text{if}\, O_j(n) - O_j(n-1) \\ = S_j(n) - S_{j+1}(n) \text{ and } j = 1 \\ \sum_j S^{P,l}_{j,S_j(n)}(n) S^P_{j+1,S_{j+1}(n)}(n), \\ \text{if}\, O_j(n) - O_j(n-1) \\ = S_j(n) - S_{j+1}(n) \text{ and} \\ j = N-1 \\ \sum_j S^{P,l}_{j,S_j(n)}(n) S^{P,r}_{j+1,S_{j+1}(n)}(n) \\ |_{S_j(n)-S_{j+1}(n)=O_j(n)-O_j(n-1)}, \\ \text{if } O_j(n) - O_j(n-1) \\ = S_j(n) - S_{j+1}(n) \text{ and } j = 2, \\ \cdots, N-2 \end{cases} \tag{3}$$

$\boldsymbol{S}_i^P(n)$ can be calculated by Equations (4–6) as follows:

$$\boldsymbol{S}_1^P(n) = \boldsymbol{SO}_1^P \tag{4}$$

$$S^{P,r}_{u,v}(n) = \begin{cases} SO^P_{u,v} \sum_{k=0}^{CA_u - v} x^P_{u,k}(n-1) + x^P_{u,v}(n-1) \\ \sum_{k=v+1}^{M_u} SO^P_{u,k},\, v = 0, 1, \cdots, M_u - 1 \\ SO^P_{u,v} \sum_{k=0}^{CA_u - l} x^P_{u,v}(n-1),\, v = M_u \end{cases}$$

$$S^{P,l}_{u,v}(n) = \begin{cases} SO^P_{u,v} \sum_{k=v}^{CA_{u-1}} x^P_{u-1,k}(n-1) + x^P_{u-1,v}(n-1) \\ \sum_{k=v+1}^{M_u} SO^P_{u,k},\, v = 0, 1, \cdots, M_u - 1 \\ SO^P_{u,v} \sum_{k=v}^{CA_{u-1}} x^P_{u-1,k}(n-1),\, v = M_u \end{cases} \tag{5}$$

$$\boldsymbol{S}_N^P(n) = \boldsymbol{SO}_N^P \tag{6}$$

where $u = 2, 3, \cdots, N-1$, upper r and l represent the right and left part of the two parts of $\boldsymbol{S}_u^P(n)$, respectively.

It shall be pointed out that each iteration step above has multiple probability multiplications and accumulations. In order to ensure the convergence of the algorithm, it needs to normalise the $\boldsymbol{x}_j^P(n)$ at the end of each cycle as follows:

$$x^P_{j,k}(n) = x^P_{j,k}(n) / \sum_{l=0}^{C_j} x^P_{j,l}(n) \tag{7}$$

where $k = 0, 1, \cdots, C_j$.

The above iterative algorithm Equation (2) also requires an initial condition. For simplicity, it assumes that the initial utilisation of each buffer is 0, i.e. $\boldsymbol{x}_j^P(0) = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}^T, j = 1, 2, \cdots, N-1$. Then, the value of $\boldsymbol{SO}_i^P$ can be calculated using Equation (8) as follows:

$$SO^P_{i,k} = C^{M_i}_k p^k (1-p)^{M_i-k} \quad (8)$$

where $k \in \{0, 1, \cdots, M_i\}$ and $i \in \{1, \cdots, N\}$.

A machine in the production line may breakdown at stage $i_1 \in \{1, \cdots, N\}$ at cycle n_1 and recovery at n_2. When the stage breaks, each value of the $\boldsymbol{SO}^P_{i_1}$ for this stage changes and can be calculated using the following equation:

$$SO^P_{i_1,k} = C^{M_{i_1}-1}_k p^k (1-p)^{M_{i_1}-1-k} \quad (9)$$

where $k \in \{0, 1, \cdots, M_{i_1} - 1\}$. The Idle-area of MB also replaces buffer T_{i_1-1} or Area $i_1 - 1$ in the same cycle. At this point, $\boldsymbol{x}^P_{i_1-1}(n_1) = [x^P_{i_1-1,0}(n_1) \quad x^P_{i_1-1,1}(n_1) \quad \cdots \quad x^P_{i_1-1,CA_{MB}}(n_1)]^T = [1 \quad 0 \quad \cdots \quad 0]^T$. Then bring all $\boldsymbol{SO}^P_i$ and $\boldsymbol{x}^P_j$ into the iterative algorithm Equation (2) and continue to run. When the stage i_1 recovery at n_2, the $\boldsymbol{SO}^P_{i_1}$ and $\boldsymbol{x}^P_{i_1-1}(n_2)$ become the same as the state at cycle $n_1 - 1$ and continue to bring in Equation (2).

Finally, $PR(n)$ can be calculated using the following equation:

$$PR(n) = \begin{bmatrix} 0 \\ 1 \cdot \sum_{k=1}^{M_N} SO^P_{N,k} \\ 1 \cdot SO^P_{N,1} + 2 \cdot \sum_{k=2}^{M_N} SO^P_{N,k} \\ \vdots \\ \sum_{k=1}^{M_N} k \times SO^P_{N,k} \end{bmatrix}^T \boldsymbol{x}^P_{N-1}(n) \quad (10)$$

Furthermore, the breakdown-free steady PR with threshold δ, SPR_δ, can be obtained as follows:

$$\mathrm{SPR}_\delta = PR(n)|_{PR(n)-PR(n-1)<\delta}, n \in N^+ \quad (11)$$

The above model refers to (Gu et al. 2015) and has been improved to make it suitable for production line with RM and MB. This model is used for production lines of 2-stage-1-buffer, 3-stage-2-buffer, 4-stage-3-buffer, and 5-stage-4-buffer, respectively. The resulting SPR_δ has an error of less than 0.5%.

2.3. Resilience indices

The resilience of a production system is measured by how does the system react when one of its stage, for instance, machine $q, q \in (1, 2, \cdots, M_i)$ at stage $i, i \in \{1, 2, \cdots, N\}$, breaks down. There are several resilience indices including:

The Production Loss (PL). The production loss is the lost due to the machine breakdown at cycle n_1. It can be calculated as follows:

$$\mathrm{PL}_{i,q} = \sum_{n=n_1}^{t_r} SPR_\delta - PR^{i,q}(n) \quad (12)$$

where the superscript i, q denote machine q at stage i, t_r is defined as the time when the $PR(n)$ is restored to the steady state after the breakdown.

The Work-In-Process (WIP) and Work-In-Process in Idle-area of Movable Buffers (WIPM). WIP is extensive used in production system engineering and can be calculated by Equation (13) as follows. In this paper, MB is added to the production system design instead of the ordinary buffer and the Idle-area of MB will be exploited to store WIP in the event of breakdown. Therefore, we call Work-In-Process in Idle-area of Movable Buffers WIPM, which can be temporarily stored in MB for late usage and calculations are similar to WIP. Define $\boldsymbol{x}^P_{\boldsymbol{MB_{i-1}}}$ as the probability of the state vector of MB, $\boldsymbol{x_{MB}}$ is the MB will replace the original buffer T_{i-1} during the breakdown. $\mathrm{WIPM}_{i,q}$, $i = 2, 3, \cdots, N$, can be calculated as follows:

$$\mathrm{WIP}_{i,q} = \sum_{k=0}^{CA_{i-1}} k \cdot x^P_{i-1,k}(t_r) \quad (13)$$

$$\mathrm{WIPM}_{i,q} = \sum_{k=0}^{CA_{MB}} k \cdot x^P_{MB_{i-1},k}(t_r) \quad (14)$$

where CA_{MB} is recorded for the capacity of MB Idle-area.

The Process Time of Work-In-Process in Idle-area of Movable Buffers with Threshold γ ($\mathrm{WIPMT}^{i,q}_\gamma$). This index is suitable for calculating additional labour costs, such as overtime costs. The calculation of $\mathrm{WIPMT}^{i,q}_\gamma$ is the same as $\mathrm{WIPM}_{i,q}$ except that the initial condition in the buffer T_{i-1} is replaced with $\mathrm{WIPM}_{i,q}$ instead of 1. The initial conditions in other buffers are 0. When the machine at the first $i - 1$ stage stops working, $\mathrm{WIPM}_{i,q}$ are processed by the latter stages. It is assumed that the production will have no more breakdowns when processing $\mathrm{WIPM}_{i,q}$ and $\mathrm{WIPTM}^{i,q}_\gamma$. The Threshold γ, which defines that if the PR is less than it at cycle n when processing $\mathrm{WIPM}_{i,q}$, then $\mathrm{WIPTM}^{i,q}_\gamma = n, n \in N^+$.

The Investment Return (IR). This is a combination of PL, $\mathrm{WIPM}_{i,q}$ and $\mathrm{WIPTM}^{i,q}_\gamma$. Assuming the cost per product is C_P and the cost per minute of overtime is C_O, IR can be calculated as follows:

$$\mathrm{IR}_{i,q} = (Y - \mathrm{PL}_{i,q} + \mathrm{WIPM}_{i,q}) \cdot C_P - \mathrm{WIPTM}^{i,q}_\gamma \cdot C_O - \mathrm{FC} \quad (15)$$

where Y is the yield without breakdown, and FC is the fixed cost of equipment and running the production line.

It shall be mentioned that production systems may breakdown in many different ways. Though, in this paper, we only considered one breakdown occurring at a time. Let the probability of breakdown at each stage of the production system be $pb_1, pb_2, \cdots, pb_N$ with $\sum_{i=1}^{N} pb_i = 1$. Further, the expectations for indices PL, WIPM and WIPTM can be obtained as follows:

$$\mathrm{PL} = \sum_{i=1}^{N} pb_i PL_{i,q}$$

$$\mathrm{WIPM} = \sum_{i=1}^{N} pb_i \mathrm{WIPM}_{i,q}$$

$$\mathrm{WIPTM} = \sum_{i=1}^{N} pb_i \mathrm{WIPTM}_{\gamma}^{i,q} \tag{16}$$

where q is a machine in stage i and $q \in \{1, 2, \cdots, M_i\}$. Accordingly, the total IR is as follows:

$$\mathrm{IR} = (Y - \mathrm{PL} + \mathrm{WIPM}) \cdot C_P - \mathrm{WIPTM}_{\gamma} \cdot C_O - \mathrm{FC} \tag{17}$$

In summary, the procedure of computing the resilience of the production is as follows:

- Step 1: Determine the production cycle time of each stage and then compute the production cycle time ΔT using Equation (1).
- Step 2: Use the iterative algorithm Equations (2–9) to calculate $\boldsymbol{x}_j^P(n), j \in \{1, 2, \cdots N-1\}$. Calculate PR and SPR_{δ} using Equations (10) and (11), respectively.
- Step 3: For a specific breakdown, compute $\mathrm{PL}_{i,q}$, $\mathrm{WIPM}_{i,q}$ and $WIPTM_{\gamma}^{i,q}$ using Equations (12–15).
- Step 4: For each possible breakdown, repeat Step 3 and Step 4.
- Step 5: Compute PL, WIPM, WIPTM and IR using Equations (16) and (17).

3. Numerical examples

In this section, we will give two numerical examples to illustrate the method, and mainly use the Matlab 2018b for programming.

3.1. A production line with three operations:

In this example, we consider a single-type product production system. The product is made in three operations: A_1, B_1, C_1. Typically, each operation is completed in a stage (i.e. Operation A_1 is completed at Stage 1, Operation B_1 is completed at Stage 2 and Operation C_1 is completed at Stage 3), and each operation requires 1 min to complete. Thus, the production cycle time is 1 min. The production system can be set up in various ways and the goal is to find the optimal setup that minimises the investment return, IR, when facing breakdown. In the study, following assumptions are made:

(1) The operation cost is calculated based on an 8-h working day. The overtime requires an additional cost 0.02/min.
(2) The fixed cost of a single-function machine is 1. The return of investment of a product is 0.08. The cost of a dual-function RM machine is 1.3 and the cost of a three-function RM machine is 1.9. The cost of a buffer is 0.2 and its capacity is 5. The cost of an MB is 0.3 and its capacity is 60. If the production system uses 1 buffer, an alternative is to use an MB which consists of two areas: Area-1 and Idle-area, and their capacities are 10 and 20, respectively. If the production system uses 2 buffers, an alternative is to use a MB consists of three areas: Area-1, Area-2 and Idle-area and their capacities are 5, 5, and 60, respectively. Some of the costs are omitted herein, such as the maintenance cost and etc.
(3) The Bernoulli reliability of a machine is 0.95. The reliability of the switch p_s in an RM is 0.99. The reliability of a MB p_{MB} is also 0.99.
(4) Suppose there are I operations $A_i, i \in \{1, 2, \cdots, I\}$, J operations $B_j, j \in \{1, 2, \cdots, J\}$ and K operations $C_k, k \in \{1, 2, \cdots, K\}$ on the production line. Operations A_i will never break. A breakdown will occur on one operation B_i or C_j and the probability are $1/(J + K)$, respectively. δ of SPR_{δ} and γ of $\mathrm{WIPTM}_{\gamma}^{i,q}$ are 0.01 and 0.2, respectively.
(5) When a breakdown is encountered, two strategies can be implemented:
Strategy 0 — waiting for the machine being repaired;
Strategy 1 — Add resilient elements RM or MB or both to the production system, RM can take 2 cycles to reconfigure the system and MB can store the WIP generated from the previous stage to the Idle-area.

Figure 5 shows seven types of configurations. Type 1 is three machines connected in series with no buffer. It is perhaps the most common configuration and can be considered as a baseline. Type 2 is similar to Type 1 but adds a buffer between Stage 1 and Stage 2 with the capacity of 10. Type 3 is also similar to Type 1 but adds two buffers and their capacities are 5. Type 4 replaces the two fixed buffers in Type 3 with one MB. The machines in Type 1, 2, 3, and 4 cannot be reconfigured.

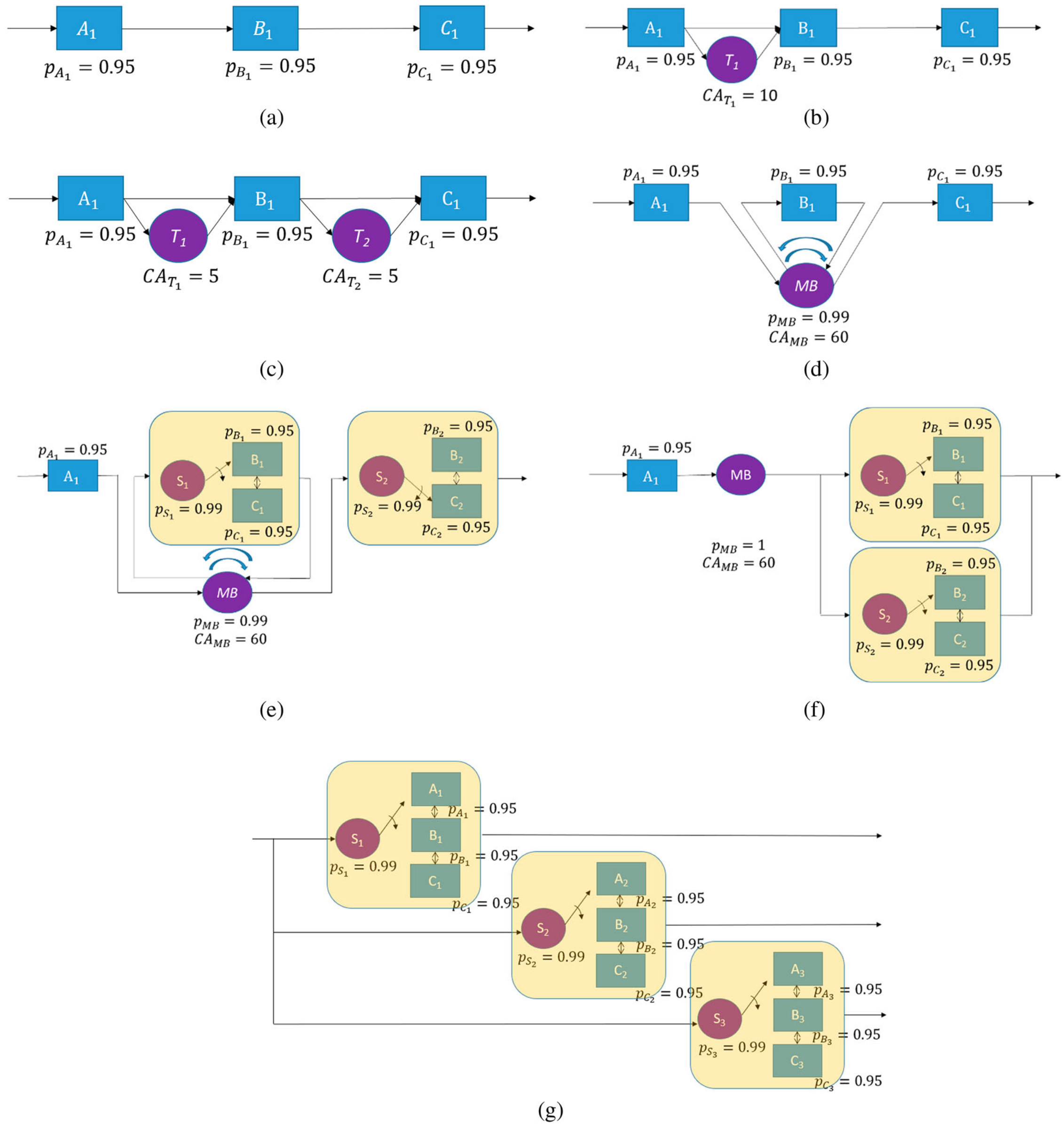


Figure 5. Seven different configurations.

Type 5 uses one machine and two RMs. Normally, the RM at Stage 2 performs operation B_1 while the RM at Stage 3 performs operation C_2. When operation B_1 in RM at Stage 2 is broken. There are two cases herein. Breakdown case 1 assumes that the operation B and operation C can be done without sequential requirement. In this case, as shown in Figure 6(a), if B_1 breaks down, the switch S_1 is switched to C_1 to carry out operation C first. Then the switch S_2 is switched to B_2 to carry out operation B. In other words, the production routine is $A_1C_1B_2$. Breakdown case 2 requires operation B and operation C being performed in a fixed order. In this case, as shown in Figure 6(b), if B_1 breaks down, with the help of MB Operation B can be performed first in B_2 followed by Operation C in the C_2. In other words, the production routine is $A_1B_2C_2$.

Type 6 links the two RMs of Type 5 in parallel and each RM performs operation B and C simultaneously. Type 7 parallels three RMs and each performs all operations simultaneously. The parallel structure of Configuration Type 6 and 7 makes it inadvisable to reconfigure the system because the internal operations of RM are performed in series when a breakdown occurs. Then Type 6 and Type 7 do not reconfigure the system and wait to be repaired if a breakdown occurs.

We calculate $PR(n)$, SPR_δ, $PR^{i,q}(n)$, $\mathrm{PL}_{i,q}$, $\mathrm{WIPM}_{i,q}$ and $WIPTM_\gamma^{i,q}$ with the method in Section 2.2. Take, for example, the calculation of the state $\boldsymbol{x}_1^P(n)$ and

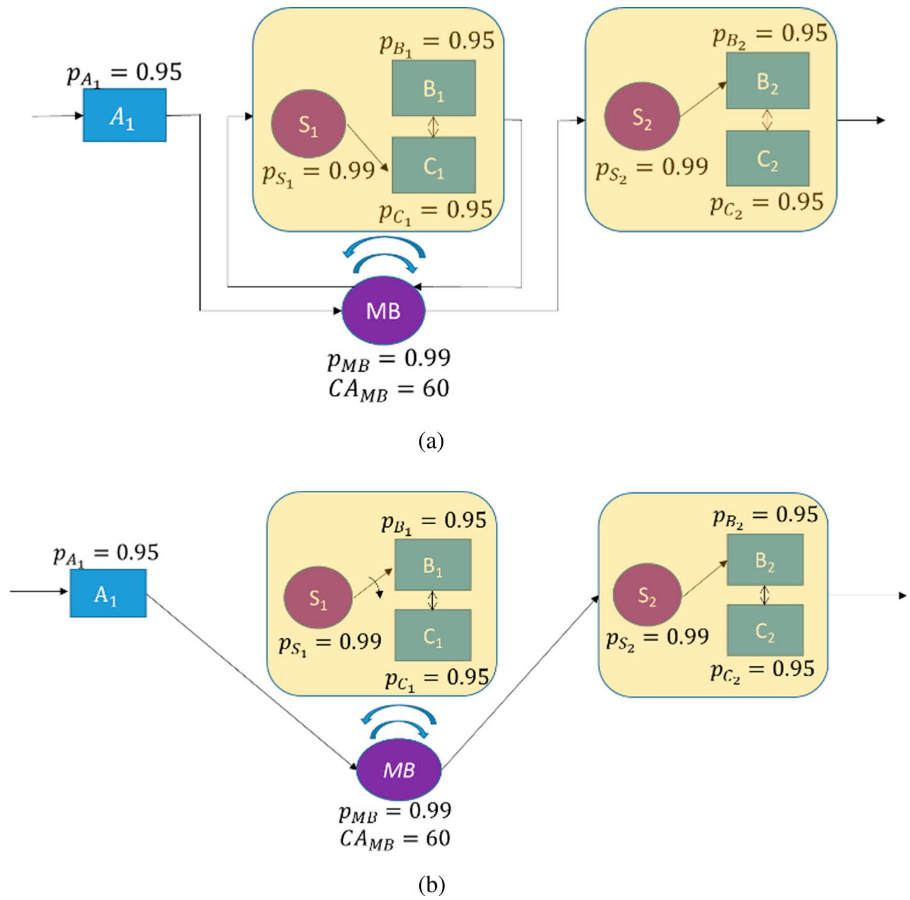


Figure 6. The production routine in Type 5 after breakdown.

$x_2^P(n)$ at cycle 1. $SO_1^P = SO_2^P = SO_3^P = [0.05 \quad 0.95]$ can be calculated by Equation (8). Then according to Equations (4–6), obtain $S_1^P(1) = S_3^P(1) = [0.05 \quad 0.95]$ and $S_2^{P,r}(1) = S_2^{P,l}(1) = [1 \quad 0]$. Finally, $x_1^P(1) = [0.05 \quad 0.95 \quad 0 \quad \cdots \quad 0]$ and $x_2^P(1) = [1 \quad 0 \quad 0 \quad \cdots \quad 0]$ can be obtained in terms of Equations (1) and (2). It is assumed that a breakdown in Operation B_i or C_j occurs at cycle 200 and recovery at the end of the 260 cycle. Note that Type 7 can be considered as one stage as it contains three RMs and each can handle three operations. Thus, the production cycle time of Type 7 is 3.

Figure 7 shows the *PR* of different types of settings. Table 1 shows their performance comparisons. Following observations can be made:

- For Type 1, if operation B_1 or C_1 breaksdown, the *PR* will go down to zero. After the breakdown is fixed, the *PR* goes back to normal again. The investment return, IR, is also low because of the low SPR_δ, high $PL_{i,q}$ and $WIPM_{i,q} = 0$.
- For Type 2, if operation B_1 or C_1 breaksdown, the *PR* goes down to zero just like that of Type 1. However, it has a buffer for cushion. Thus, its SPR_δ is higher than that of Type 1. Its PL is slightly higher because of the higher SPR_δ. Though, the higher SPR_δ results in better IR than that of Type 1.
- For Type 3, if operation B_1 breaksdown, the production system can continue to run until the parts in buffer T_2 runs out, then the *PR* goes down to zero gradually. Similarly, if operation C_1 breaks down, the *PR* goes down to zero. Type 3 has two buffers for cushion. Hence, its SPR_δ is higher than that of Type 2. Though, the capital investment also increases. Because of the increase of SPR_δ, its IR increases.
- For Type 4, during breakdowns, its *PR* is rather similar to that of Type 3. However, it SPR_δ is less than that of Type 3 because the MB is unreliable. The MB does not affect PL. Furthermore, since MB increases $WIPM_{i,q}$, its IR is better than that of Type 3. In practice, though, the cost, FC, should be carefully considered.
- For Type 5, when Strategy 0 is taken during the breakdown, the *PR* is also reduced to 0. However, the *PR* can quickly bounce back as the system can be reconfigured. When Strategy 1 is taken during the breakdown, the system keeps on working (though with reduced rate). This applies to both operation B_1 breaks down and operation C_2 breaks down. Its SPR_δ is

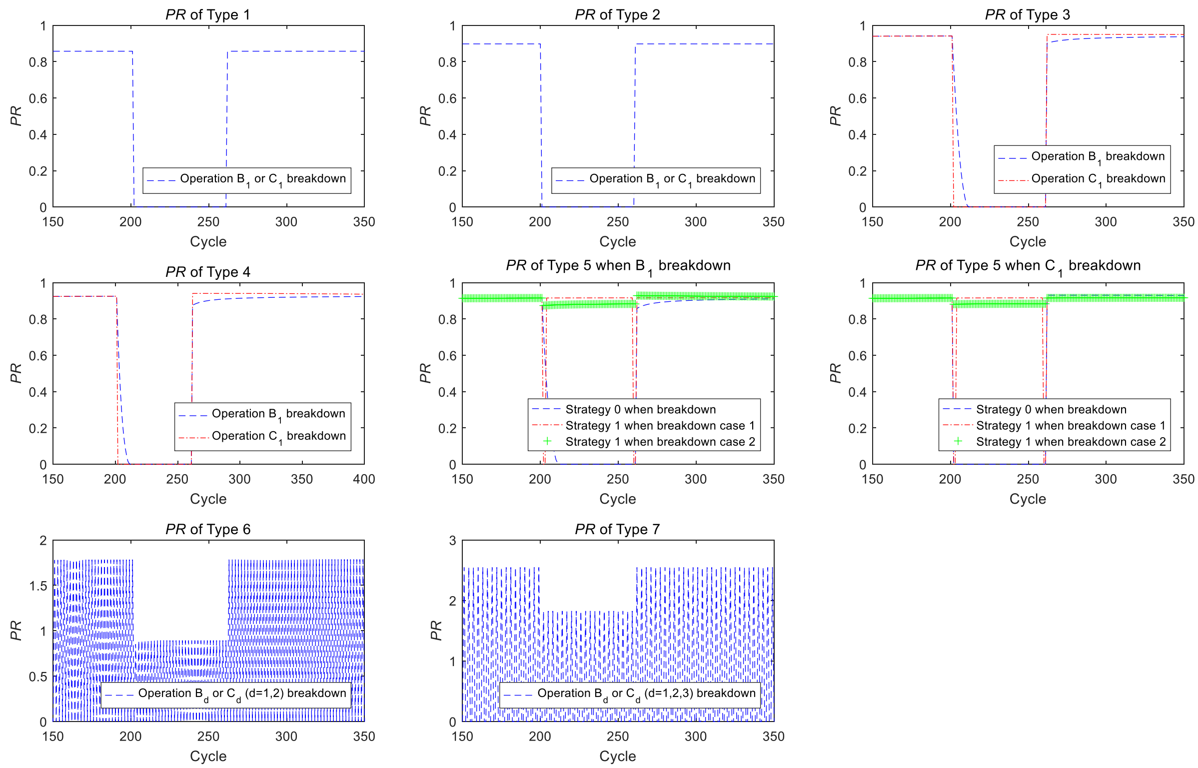


Figure 7. The PR of seven different configurations.

Table 1. The performance comparison among the seven kinds of configurations.

		Breakdown operation	SPR_δ	$PL_{i,q}$	$WIPM_{i,q}$	$WIPTM_{\gamma}^{i,q}$/min	IR
Type 1		B or C	0.8574	51.44	0	0	25.81
Type 2		B or C	0.8978	54.01	0	0	26.95
Type 3		B	0.9448	55.17	0	0	28.48
		C		54.57	0	0	
Type 4		B	0.9333	54.82	56.43	65	31.37
		C		54.8	55.44	60	
Type 5	Strategy 0	B_1	0.9098	54.18	56.43	66	30.39
		C_2		54.16	55.02	61	
	Strategy 1 for Case 1	B_1		3.64	0	0	31.25
		C_2		3.64	0	0	
	Strategy 1 for Case 2	B_1		5.21	4.72	8	31.34
		C_2		5.21	4.72	8	
Type 6		B_d or C_d (d = 1, 2)	0.8931	26.78	38.3	47	28.14
Type 7		B_d or C_d(d = 1, 2, 3)	0.8488	14.41	0	0	25.74

less than that of Type 4 because RM is less reliable. The $PL_{i,q}$ is mainly due to the system reconfiguration. When operation B_1 breaks down, the system returns to the full capacity after reconfiguration. This helps to place its IR 9.73% higher than that of Type 3 ((31.25 − 28.48/28.48)% = 9.73%).

- For Type 6, the *PR* does not drop to 0 during the breakdown because there are always other parallel machines working. It is interesting to note that its *PR* jumps up and down. This is because the cycle time of stage 2 is 2 min while the production cycle time is 1 min. Although the MB keeps on serving both RMs, *PR* will be interrupted. Consequently, its SPR_δ is lower even though its reliability is high. Its IR is also lower.
- For Type 7, similar to Type 6, the *PR* does not drop to 0 during the breakdown. However, its SPR_δ is low for the same reason. Additionally, its FC is higher and hence, the IR is low.

In summary, both Type 4 and Type 5 are good choices. This implies that both RM and MB will help to gain higher IR and increase the resilience of production line. Though, too many RM could result in reduced *PR* and hence, is not desirable.

3.2. A production line with 10 operations

This example is a 10-stage serial production line as shown in Figure 8(a). Each stage deals with an operation. The

Table 2. The number of machines in each stage and the corresponding Bernoulli reliability.

Stage	1	2	3	4	5	6	7	8	9	10
Number of machines	2	2	1	1	2	3	1	1	1	2
Bernoulli reliability	0.7	0.7	0.9	0.9	0.7	0.55	0.9	0.9	0.9	0.7

goal is to add RM and MB to the system to increase the system resilience. Following assumptions are made except for those in Section 2.2.

(1) The number of machines per stage and the corresponding Bernoulli reliability are shown in Table 2;
(2) Each operation needs 1 min to finish and each reconfiguring of RM takes 5 min. $p_s = 0.99$ and $p_{MB} = 1$;
(3) The machine in 4th, 8th, 9th stages may occur a breakdown and the probabilities are 0.2, 0.4 and 0.4, respectively. The breakdown will last 500 min;
(4) The cost of a single function machine, FC, is 1. The investment return, IR, of a product is 0.021 and the WIPTM cost is 0.009 per minute. The cost of a dual-function RM machine is 1.6. A normal buffer with a capacity of 10 costs 0.2. The cost of $MB_k, k \in \{1, 2, 3\}$ is 0.5 and the capacities of it are Area 1 = 10, Area 2 = 10, Area 3 = 10 and Idle-area = 600;
(5) The production time excluding WIPTM, PT, is 4800 min. δ of SPR_δ and γ of $\text{WIPTM}_\gamma^{i,q}$ are 0.01.

Based on Section 3.1, the RM is best positioned on one of the two sides of the breakdown stage. MB should place the WIPs generated by stage $i-1, i\ i \in \{1, 2, \cdots, 10\}$ in the Idle-area when stage i breakdown. MB can replace buffer $T_j, j \in \{1, 2, \cdots, 9\}$ from beginning to end because cost of that is less than the sum of three buffers and reliability probability of MB is 1.

The initial configuration and three improved configurations as shown in Figure 8(a–d) are proposed and compared to find the optimal one.

As shown in Figure 8(b), MB_1 replaces buffer T_1 to T_3, MB_2 replaces buffer T_4 to T_6 and MB_3 replaces buffer T_7 to T_9 in Type 2.

As shown in Figure 8(c), replace three machines with three RMs in Type 3. Each RM can perform 2 operations. When there is no breakdown, the production system runs in sequential order. When the 4th stage breaks down, the system is reconfigured so that Stage 3 will carry out both the 3rd and the 4th operations while the others remain unchanged. A similar strategy is applied for the breakdowns in the other stages.

As shown in Figure 8(d), Type 4 combines Type 2 and Type 3, i.e. replacing $T_j, j \in \{1, 2, \cdots, 9\}$ with $MB_k, k \in \{1, 2, 3\}$ and replacing the normal machine $M_{3,1}$, $M_{7,1}$, and $M_{8,1}$ with $RM_{3,1}^{3,4}$, $RM_{7,1}^{7,8}$, and $RM_{8,1}^{8,9}$, respectively. When a breakdown occurs, if the RM stage is less productive at the time of reconfiguring or after completion than in the previous stage, the WIP generated by the previous stage will be placed in the Idle-area of the MB.

The cycle time of each type, T, is 1 because the previous assumption mentions that each stage processing operation takes 1 min. In this example, the iterative algorithm of Section 2.2 is used to estimate dynamic performance.

Table 3 shows the performance comparison of the three configurations. From the table, following observations can be made:

- For Type 1, it has high SPR_δ because the 16 single-function machines and 9 buffers are efficient. However, it has high $\text{PL}_{i,q}$ as well no matter which stage breaks because the production system will stop when a machine breaks down and the buffers are run out of spare parts. Its $\text{WIPM}_{i,q}$ and $\text{WIPTM}_\gamma^{i,q}$ are zero because MB is not used.
- For Type 2, SPR_δ is the same as Type 1 because MB is completely reliable. Its $\text{PL}_{i,q}$ is still high. However, because of the use of MB, its $\text{WIPM}_{i,q}$ increases resulting higher IR than that of Type 1.
- For Type 3, SPR_δ is lower than that of Type 1 and Type 2 because the RM is less reliable than of the single operation machine. Though, because of the use of RM, its $\text{WIPM}_{i,q}$ is much smaller than Type 1 and 2. The MB is not adopted in this type, then $\text{WIPM}_{i,q}$ and $\text{WIPTM}_\gamma^{i,q}$ are zero. Consequently, its IR is increased a higher than of Type 2. In fact, it gives the best IR among all the configurations. A careful examination reveals that RM reduces PL during breakdown periods, while MB reduces PL by temporarily storing WIP.
- For Type 4, SPR_δ lower than that of Type 1and 2 and 3. The $\text{PL}_{i,q}$ is higher than Type 3 because the used capacity of the MB idle area at the beginning of the breakdown is 0 and it will take time to steady. The larger $\text{WIPM}_{i,q}$ and $\text{WIPTM}_\gamma^{i,q}$ for the Stage 4 breakdown is due to the higher production in the Stage 1 and 2. All WIPs produced in the second stage are placed in the Idle-area of MB after the Buffer T_2 is replaced by it. IR is the highest of the four configurations due to the utilisation of RM and MB.

In summary, the IRs of Type 2, 3, and 4 are more than 10% higher than that of Type 1. Particularly, Type 4 is the

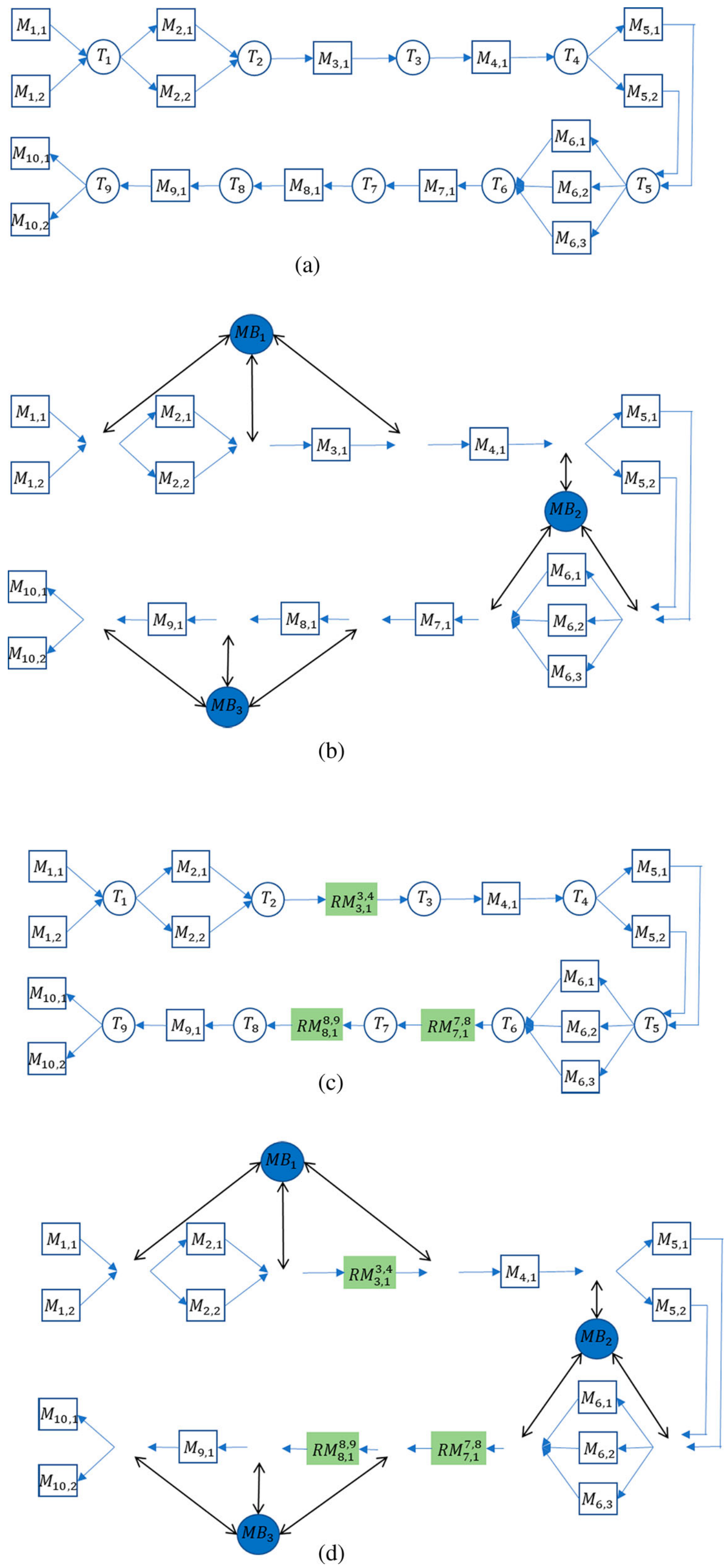


Figure 8. Different configurations. In the figure, the MBs are marked in blue and the RMs are marked in green. The subscript is the machine number of the stage while the superscript is the operation, for example, $RM_{3,1}^{3,4}$ implies this RM machine number is 1 and used in stage 3, and can carry out operations 3 and 4.

Table 3. The performance comparison among of the four configurations.

	Breakdown stage	SPR_δ	$PL_{i,q}$	$WIPM_{i,q}$	$WIPTM_\gamma^{i,q}$/min	IR
Type 1	4	0.8860	443.66	0	0	46.83
	8	443.66	0	0		
	9	443.66	0	0		
Type 2	4	0.8860	443.66	450	508	51.99
	8	443.66	445.51	503		
	9	443.66	447.53	504		
Type 3	4	0.8782	30.45	0	0	52.80
	8	45.71	0	0		
	9	47.99	0	0		
Type 4	4	0.8782	31.39	276.49	359	54.07
	8	47.1	48.00	75		
	9	49.54	46.33	67		

best choice. This indicates that the use of RM and MB helps to improve the resilience of the production system. The conclusions of this example are supported by the parameter assumptions at the beginning of this section. We are concerned about the impact of changes in two types of parameters on decision-making. One is the cost of a single RM (*CM*), which is one parameter of RM, and the other is the cost of a single MB (*CMB*) and C_O, which are two parameters of MB. Figure 9 shows the IR at different parameter values. Figure 9(a) indicates that, the IR of Type 4 remains high despite *CM* changes to 2 (*CM* should not exceed the cost of two normal machines) when the other parameters remain unchanged. However, the decision priority for Type 3 is reduced to after Type 2 when the *CM* is greater than 1.87. In Figure 9(b), Type 1 and 2 are not affected by *CMB* and C_O because they do not have MB. Type 4 is more stable than Type 2, but Type 2 has a higher IR value if (*CMB*, C_O) is to the right of Line 4. Finally, Type 3 should be adopted when (*CMB*, C_O) is to the left of line 2, Type 4 should be adopted when (*CMB*, C_O) is between line 2 and line 4, and Type 2 should be adopted when (*CMB*, C_O) is to the right of line 4.

4. Conclusions and future work

This paper presents a study on the design of resilient production system using RM and MB. The main contribution is to present an approach to model the production system with RM and MB, and RM and/or MB can improve the resilience of the production system and both are used for better results. The presented model is used to analyse two production systems, one has three operations and the other 10 operations. Based on the computer simulation, some recommendations for designing resilient production systems using RM and MB are as follows:

(1) The use of RM can effectively keep the production system running during the breakdowns and hence, reduce the production loss, PL. This helps to increase the resilience (The IR has improved over 9%) of the production system.
(2) The use of MB can effectively store Work-In-Process parts. During the breakdowns, it can keep the production system running for a period of time and hence, reduce the production loss, PL. This helps to increase the resilience (The IR has improved over 9%) of the production system.
(3) The presented iterative algorithm can effectively cut down the computation load and the resulting errors are small.
(4) In general, for complicated production systems that may have a large number of configurations, following design principles may be exercised: (1) Place RM on the bottleneck operations; (2) Placing MB requires that the routes contain the breakdown prone stage; (3) The cost of RM need to be taken into account because it could increase non-linearly; (4) The cost of handling work-in-process in movable buffers (WIPM) also needs to be considered because it could increase nonlinearly.

Designing a resilient production system needs to consider several other factors. Future research includes (1) considering the situations of multiple breakdowns occurring randomly and/or simultaneously; (2) considering the production system with more operations can produce multiple types of products; (3) considering the incoming materials/parts to the production system; (4) considering the production systems that can change their layouts; (5) considering adding more resilient elements (analogy to reconfigurable machines and movable buffers) in the supply chain; and (6) considering establishing the structural design of the real reconfigurable machines and movable buffers, platform to control the indices of resilience, etc.

Disclosure statement

No potential conflict of interest was reported by the author(s).

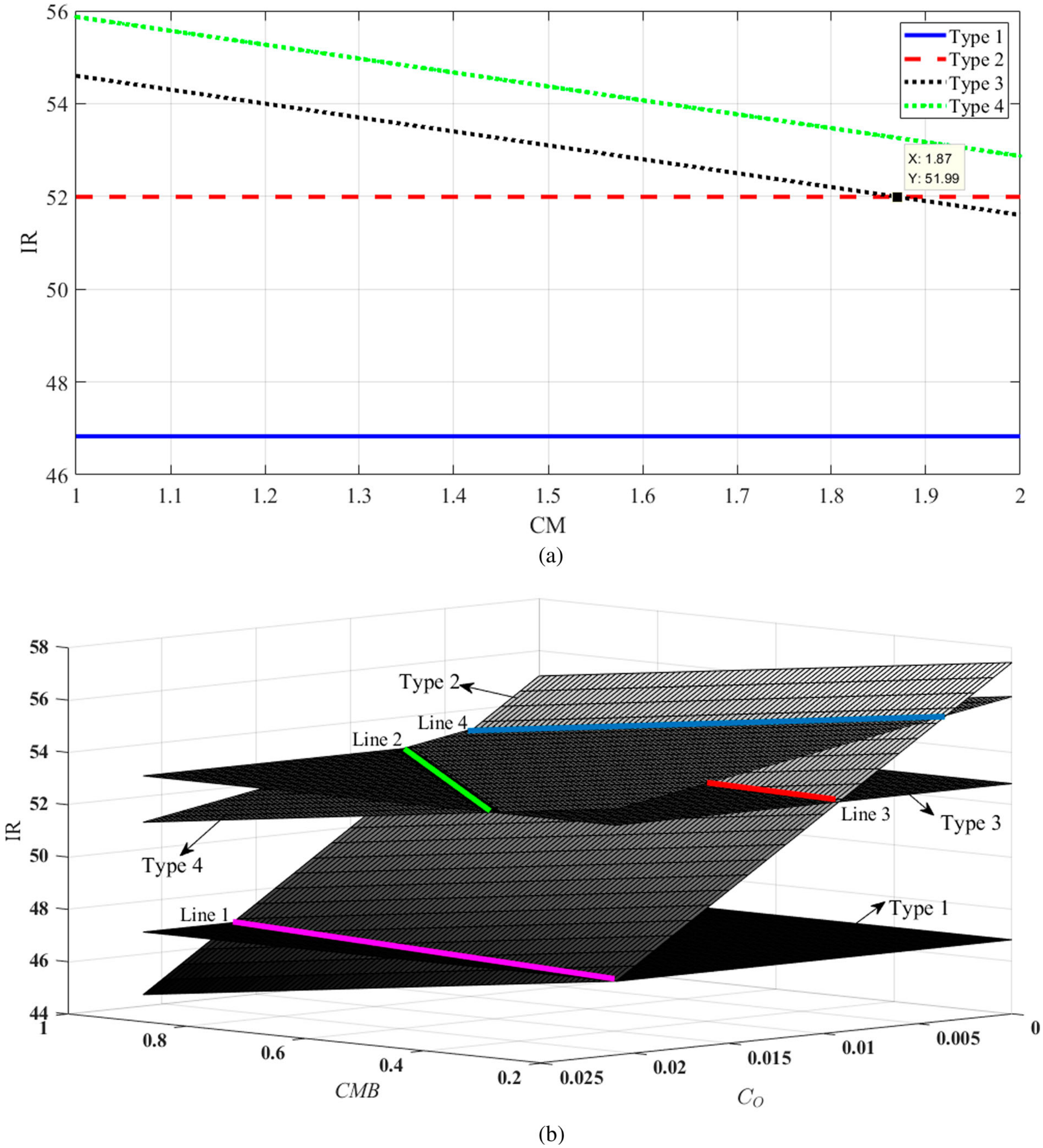


Figure 9. The value of IR when the parameters change.

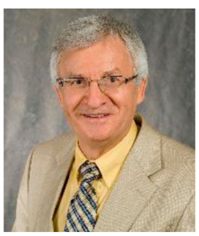
Funding

Research was supported by the Natural Science Foundation of Guangdong Province [grant number 2020A1515010621], the Opening Project of National and local joint Engineering Research Center for industrial friction and lubrication technology (2021-GD-0005) [grant number GDNRC[2020]031], Science and Technology Program of Guangzhou [grant number 202102020360], and the Strategic Priority Research Program of the Chinese Academy of Sciences (class A) [grant number XDA22040203].

Notes on contributors

Tong Qin received the B.S. degree in information and computing science from North China University of Water Resources and Electric Power, Zhengzhou, China, in 2017. He is currently a Ph.D. candidate with the Shien-Ming Wu School of Intelligent Engineering, South China University of Technology, Guangzhou, China. His main research focuses on designing and optimisation of production systems and job-shop scheduling.

Ruxu Du received the M.S. degree in automatic control from the South China University of Technology, Guangzhou, China, in 1983, and the Ph.D. degree in mechanical engineering from the University of Michigan, Ann Arbor, MI, USA, in 1989. From 1991 to 2001, he taught at the University of Windsor, Windsor, ON, Canada; at the University of Miami, Coral Gables, FL, USA; and at Chinese University of Hong Kong (CUHK), Shatin, Hong Kong. Since 2002, he has been a Professor with the Department of Mechanical and Automation Engineering, and the Director of the Institute of Precision Engineering, CUHK. He is currently a Professor with Shien-Ming Wu School of Intelligent Engineering, South China University of Technology. His research interests include precision engineering, condition monitoring, fault diagnosis, manufacturing processes (metal forming, machining, plastic injection moulding, etc.), and robotics. Dr Du became a Fellow of the America Society of Mechanical Engineers (ASME) in 2009, a Fellow of the Society of Manufacturing Engineers (SME), and the Hong Kong Institute of Engineers (HKIE) in 2012, and an Academician of Canadian Academy of Engineering in 2017.



Andrew Kusiak received the M.S. degree in mechanical engineering from the Warsaw Technical University in 1974, and the Ph.D. in operations research from the Polish Academy of Sciences in 1979. He is a Fellow of the Institute of Industrial Engineers and the Editor-in-Chief of the Journal of Intelligent Manufacturing. His past academic appointments include the Technical University of Nova Scotia (now Dalhousie University) and the University of Manitoba in Canada. He has held distinguished research professorships at the Huazhong University of Science and Technology (China), University of Hong Kong (SAR), and King Abdulaziz University (Saudi Arabia) as well as visiting positions at the University of Lion, Institut National Polytechnique de Grenoble, University of Nancy (France), and the University of Montreal (Canada). Dr Andrew Kusiak is currently a Professor in the Department of Mechanical and Industrial Engineering at The University of Iowa, Iowa City and Director of the Intelligent Systems Laboratory. His current research interests include applications of computational intelligence and big data in automation, manufacturing, product development, renewable energy, sustainability, and healthcare.

Hui Tao received the M.S. degree in control theory and control engineering from Wuhan University of Science and Technology, Wuhan, China, in 2011. He is currently a Ph.D. candidate with the Shien-Ming Wu School of Intelligent Engineering, South China University of Technology, Guangzhou, China. His main research focuses on intelligent monitoring, diagnosis and control.

Yong Zhong (S'12–M'17) received the B.Eng. degree in mechanical design, manufacturing and automation from the Huazhong University of Science and Technology, Hubei, China, in 2011, and the M.Eng. degree in control engineering from the University of Chinese Academy of Sciences, Beijing, China, in 2014, and the Ph.D. degree in Mechanical and Automation Engineering from the Chinese University of Hong Kong, Shatin, Hong Kong, in 2017. He was a research fellow at National University of Singapore from 2017 to 2019. He is currently an Assistant Professor with Shien-Ming Wu School of Intelligent Engineering, South China University of Technology. His research interests include bioinspired robots, soft robots, production system, intelligent diagnosis and control.

ORCID

Andrew Kusiak http://orcid.org/0000-0003-4393-1385
Yong Zhong http://orcid.org/0000-0002-2673-856X

References

Alliance. 2021. Resilience Key Concepts [EB/OL].

Bi, Z. M., Sherman Y. T. Lang, M. Verner, and P. Orban. 2007. "Development of Reconfigurable Machines." *The International Journal of Advanced Manufacturing Technology* 39 (11-12): 1227–1251. doi:10.1007/s00170-007-1288-1

Cavalcante, Ian M., Enzo M. Frazzon, Fernando A. Forcellini, and Dmitry Ivanov. 2019. "A Supervised Machine Learning Approach to Data-Driven Simulation of Resilient Supplier Selection in Digital Manufacturing." *International Journal of Information Management* 49: 86–97. doi:10.1016/j.ijinfomgt.2019.03.004

Chang, Tien-Hsiang, Hsin-Pin Fu, and Kuan-Yu Hu. 2006. "Innovative Application of an Integrated Multi-Level Conveying Device to a Mobile Storage System." *The International Journal of Advanced Manufacturing Technology* 29 (9-10): 962–968. doi:10.1007/s00170-005-2607-z

Coughlin, Tom. 2011. "Thailand Floods Will Impact Hard Disk Drive Components."

D'Souza, Floyd, João Costa, and J. N. Pires. 2020. "Development of a Solution for Adding a Collaborative Robot to an Industrial AGV." *Industrial Robot: the International Journal of Robotics Research and Application* 47 (5): 723–735. doi:10.1108/ir-01-2020-0004

Dinh, Linh T. T., Hans Pasman, Xiaodan Gao, and M. Sam Mannan. 2012. "Resilience Engineering of Industrial Processes: Principles and Contributing Factors." *Journal of Loss Prevention in the Process Industries* 25 (2): 233–241. doi:10.1016/j.jlp.2011.09.003

Gadalla, Moustafa, and Deyi Xue. 2018. "An Approach to Identify the Optimal Configurations and Reconfiguration Processes for Design of Reconfigurable Machine Tools." *International Journal of Production Research* 56 (11): 3880–3900. doi: 10.1080/00207543.2017.1406674

Gao, Hai-Xiang, Ying Chen, Shao-Wei Huang, and Yin Xu. 2015. "Distribution Systems Resilience: an Overview of

Research Progress." *Automation of Electric Power Systems* 39 (23): 1–8. doi: 10.7500/AEPS20150717002

Gu, Xi, Xiaoning Jin, Jun Ni, and Yoram Koren. 2015. "Manufacturing System Design for Resilience." *Procedia CIRP* 36: 135–140. doi:10.1016/j.procir.2015.02.075

Haug, Anders. 2018. "Defining 'Resilient Design' in the Context of Consumer Products." *The Design Journal* 21 (1): 15–36. doi:10.1080/14606925.2018.1395265

Hollnagel, Erik. 2012. *FRAM: The Functional Resonance Analysis Method: Modelling Complex Socio-Technical Systems*. Boca Raton: CRC Press.

Jin, Xiaoning, and Gu Xi. 2016. "Option-Based Design for Resilient Manufacturing Systems." *IFAC-PapersOnLine* 49 (45): 1602–1607. doi:10.1016/j.ifacol.2016.07.809

Kakadia, Deepak, and Jose Emmanuel Ramirez-Marquez. 2020. "Machine Learning Approaches for Network Resiliency Optimization for Service Provider Networks." *Computers & Industrial Engineering* 146: 106519-1–106519-19. doi:10.1016/j.cie.2020.106519

Katz, Reuven. 2007. "Design Principles of Reconfigurable Machines." *The International Journal of Advanced Manufacturing Technology* 34 (5-6): 430–439. doi:10.1007/s00170-006-0615-2

Koren, Y., U. Heise, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, and H. Van Brussel. 2003. *Reconfigurable Manufacturing Systems*. Berlin, Heidelberg: Springer.

Kusiak, Andrew. 2019. "Fundamentals of Smart Manufacturing: A Multi-Thread Perspective." *Annual Reviews in Control* 47: 214–220. doi:10.1016/j.arcontrol.2019.02.001

Kusiak, Andrew. 2020. "Resilient Manufacturing." *Journal of Intelligent Manufacturing* 31 (2): 269–269. doi: 10.1007/s10845-019-01523-7

Mattsson, Lars-Göran, and Erik Jenelius. 2015. "Vulnerability and Resilience of Transport Systems – A Discussion of Recent Research." *Transportation Research Part A: Policy and Practice* 81: 16–34. doi:10.1016/j.tra.2015.06.002

Meerkov, Semyon M., and Liang Zhang. 2008. "Transient Behavior of Serial Production Lines with Bernoulli Machines." *IIE Transactions* 40 (3): 297–312. doi:10.1080/07408170701488037

Müller, F., M. Bergmann, R. Dannowski, J. W. Dippner, A. Gnauck, P. Haase, Marc C. Jochimsen, et al. 2016. "Assessing Resilience in Long-Term Ecological Data Sets." *Ecological Indicators* 65: 10–43. doi:10.1016/j.ecolind.2015.10.066

Ouyang, Min, Leonardo Dueñas-Osorio, and Xing Min. 2012. "A Three-Stage Resilience Analysis Framework for Urban Infrastructure Systems." *Structural Safety* 36-37: 23–31. doi:10.1016/j.strusafe.2011.12.004

Sawik, Tadeusz. 2018. *Supply Chain Disruption Management Using Stochastic Mixed Integer Programming. Vol. 256*. Switzerland: Springer International Publishing.

Simmie, J., and R. Martin. 2010. "The Economic Resilience of Regions: Towards an Evolutionary Approach." *Cambridge Journal of Regions, Economy and Society* 3 (1): 27–43. doi:10.1093/cjres/rsp029

Tendall, D. M., J. Joerin, B. Kopainsky, P. Edwards, A. Shreck, Q. B. Le, P. Kruetli, M. Grant, and J. Six. 2015. "Food System Resilience: Defining the Concept." *Global Food Security* 6: 17–23. doi:10.1016/j.gfs.2015.08.001

Tian, Bo, Xichang Liang, and Jisheng Pan. 2007. "Automatic Working Machine Tools of Wheel Rims Based on Reconfiguration." *Chinese Journal of Mechanical Engineering* 43 (6): 246–225. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFQ&dbname=CJFD2007&filename=JXXB200706040&v=MDI1MDNVUjdxZlkrUm9GeTdrVTd2SUx6WFRiTEc0SHRiTXFZOUJaSVI4ZVgxTHV4WVM3RGgxVDNxVHJXTTFGckM=.

Wan, Samuel. 2016. "Taiwan Earthquake Will Affect TSMC Fab More Than Expected.".

Xi, Ju-Zhe, Zhi-Hong Zuo, and Wei Wu. 2012. "Approaches to Research on Resilience." *Advances in Psychological Science* 20 (9): 1426–1447. doi:10.3724/sp.J.1042.2012.01426

Zhang, W. J., and C. A. van Luttervelt. 2011. "Toward a Resilient Manufacturing System." *CIRP Annals* 60 (1): 469–472. doi:10.1016/j.cirp.2011.03.041

Zhang, Liang, Chuanfeng Wang, Jorge Arinez, and Stephan Biller. 2013. "Transient Analysis of Bernoulli Serial Lines: Performance Evaluation and System-Theoretic Properties." *IIE Transactions* 45 (5): 528–543. doi:10.1080/0740817x.2012.721946

Zou, Jing, Qing Chang, Xinyan Ou, Jorge Arinez, and Guoxian Xiao. 2019. "Resilient Adaptive Control Based on Renewal Particle Swarm Optimization to Improve Production System Energy Efficiency." *Journal of Manufacturing Systems* 50: 135–145. doi:10.1016/j.jmsy.2018.12.007