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Manufacturing System Design for Resilience

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Abstract

Unexpected disruptive events in manufacturing systems always interrupt normal production conditions and cause production loss. A resilient system should be designed with the capability to suffer minimum production loss during disruptions, and settle itself to the steady state quickly after each disruption. In this paper, we define production loss (*PL*), throughput settling time (*TST*), and total underproduction time (*TUT*) as three metrics to measure system resilience, and use these measures to assist the design of multi-stage reconfigurable manufacturing systems. Numerical case studies are conducted to investigate how the system resilience is affected by different design factors, including system configuration, level of redundancy or flexibility, and buffer capacities.

Keywords: resilience; manufacturing system design

1. Introduction

Modern manufacturing systems consist of machines, inspection stations and intermediate buffers, that are interconnected to perform required production operations. A disruptive event (such as machine failure) could lead to full or partial loss of production in the system. Therefore, gaining fundamental understanding and evaluation of disruptive events and associated impacts on system performance will have significant impact on the economic sustainability of the manufacturing enterprises.

Nomenclature

I	number of stages of the system
i_d	the index of the stage where the disruption occurs
S_i	number of machines in stage i
$T_i(k)$	cycle time for each machine at stage i at time k
C_i	capacity of buffer B_i
$N_i(k)$	the level of buffer B_i at the end of time k
$r_i(j,k)$	the probability that there are j machines in stage i that are *available* at the beginning of time k
$r_i^{NS}(j,k)$	the probability that there are j machines in stage i\ that are *available and not starved* at the beginning of time k
$r_i^{NB}(j,k)$	the probability that there are j machines in stage i that are *available and not blocked* at the beginning of time k
t_D	duration of the disruption
t_R	duration of reconfiguration

Resilience is defined as the ability of a system to withstand potentially high-impact disruptions, and it is characterized by the capability of the system to mitigate or absorb the impact of disruptions, and quickly recover to normal conditions. For example, built-in redundancy and flexibility of a system enables it to resume production from machine faults or failures by task rescheduling, workload reallocation, etc. Such capability plays an important role in manufacturing system design, operation and life management against disruptive and adverse events [1].

The research on manufacturing system resilience hasn't attracted much attention until recent years when there are increasing occurrences of disasters and hazards [2]. Most of the studies have focused on a variety of external disruptive events to the manufacturing systems ranging from natural disasters (e.g., hurricanes, earthquakes) to man-made accidents (e.g., terrorism, supplier bankrupt). Many of these studies focus on supply chain networks where risk/disaster management tools are developed to reduce impact of supply chain disruptions [3]. Nevertheless, methods for intrinsic resilience with regard to internal disruptions, such as machine failure or unscheduled downtime, are still lacking.

Therefore, modeling and analysis of manufacturing system resilience is of significant importance to manufacturing enterprise systems design and operations management in a

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dynamic global environment. The goal of this paper is to contribute to gaining fundamental understanding of manufacturing systems resilience by developing methods and tools to evaluate capabilities of fault-tolerance, performance recovery and achieving high resilience. The insights from this paper will provide fundamental principles and guidelines for the optimal design for resilience of system configurations, investment decisions on built-in redundancy and flexibility, and control strategies for risk mitigation.

In this paper, we consider an unexpected disruptive event that occurs on one machine and causes the machine to be down for a certain period. It may be an unexpected downtime or a planned downtime based on the machine degradation [4]. When the disruption ends, the machine resumes to its normal working condition and the system recovery starts. The system will eventually return to its steady state again. Impact of the disruption could be reflected in various system performance measures, such as reduced throughput and higher work-in-process. As an example, Fig. 1 shows how the throughput evolves over time when an unexpected disruption occurs. It also demonstrates that the disruption on one machine may cause production losses in the entire system. In this problem setting, the production loss can be evaluated through two stages [5]. The first stage is the time during the disruption and the second stage is from the time when disruption ends until the time the system fully recovers. Naturally, one may ask: what is the production loss caused by the disruption? How long will it take for the system to recover to its steady state? What is the total time in which the system throughput is below the planned level? To answer these questions, we study in this paper three resilience measures: *production loss* (*PL*), *throughput settling time* (TST_ε) and *total underproduction time* (TUT_ε). When disruption occurs, a resilient system should have smaller values of these three measures than a system that is not resilient.

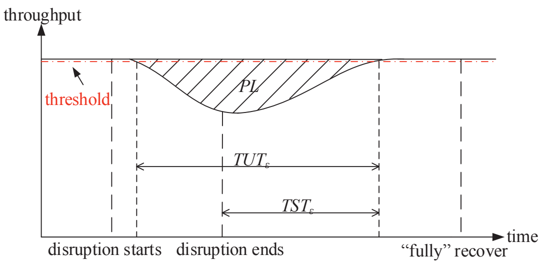

Fig. 1. Disruption profile and resilience measures

A resilient system should be designed with the capability to mitigate the effect of the disruption. Such capability mainly comes from the redundancy and flexibility embedded in the system. In this paper, we consider two control policies, both enabled by these built-in capabilities. The first policy is to increase the speed of the other machines in the system when the disruption occurs. North American automotive factories operate typically at efficiency levels of 60 - 70%, so if necessary, there often exists an opportunity to increase the speed of machines [6]. We regard such capability as system redundancy, because in a normal condition the system is not operating at its full capability. The second policy we consider in this paper is system reconfiguration, which takes advantage of the system flexible architecture. Reconfigurable manufacturing system (RMS), introduced by Koren *et al.* [7], is a system that can rapidly and cost-effectively adjust its production resources in response to unpredictable market changes and intrinsic system events [8-9]. The RMS has the capability to scale up production by adding production machines, reallocate the tasks and rebalance itself when higher throughput is needed [10-12]. Design for resilience also requires rapid adjustment of production resources by performing task reallocation and rebalancing.

Performance of manufacturing systems depends heavily on the configurations [13], which can be classified into cell configurations (i.e., several serial lines arranged in parallel without crossovers), RMS configurations (i.e., multiple stages connected by crossovers), and hybrid configurations (i.e., a combinations of the previous two classes) [7]. In this paper, we study the systems designed with RMS configurations, and with buffers between stages. These built-in buffers may delay or mitigate the propagation of the disruption [14, 15]. Moreover, since our interest is the behavior of the system under disruptions, we focus more on the transient behavior of the system, which is relatively unexplored compared to the steady-state behavior of the system.

The remaining of the paper is organized as follows. In Section 2, the model of the system is built and the resilience measures are evaluated. Section 3 is a case study where we investigate how the system resilience measures are affected by different factors. Section 4 is the conclusion.

2. Model and method

2.1. Assumptions

We consider an I-stage reconfigurable manufacturing system as shown in Fig. 2. The assumptions of the system are:

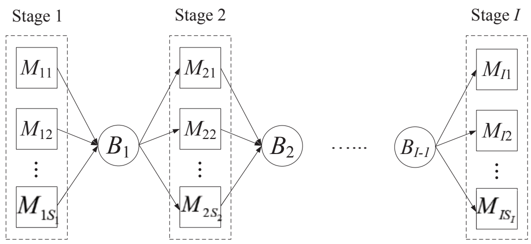

Fig. 2. An I-stage system

- The machines in the same stage work synchronously. They are *available* (i.e. can change the system dynamics) only at the beginning of one cycle of that stage.
- In every cycle, each machine in stage i is "up" with probability p_i, and "down" with probability $1-p_i$.
- If the number of available machines in stage S_i is larger than the number of parts in buffer B_{i-1}, then the excessive machines will be starved; if the number of available machines in stage i is larger than the available spaces in buffer B_i (after the non-starvation machines in stage i+1 have taken some parts out from B_i), the excessive machines

will be blocked. The machines in stage 1 are never starved and that in stage I are never blocked.

- Only one disruptive event is considered, which occurs when the system is in its steady state.
- The required production rate is constant and equal to the steady-state system production rate.

2.2. System dynamics

The system follows a Bernoulli reliability model, which fits real production practice where the machine downtime is resulted mainly from quality problems. Extensive work has been done to on the serial Bernoulli lines with an identical cycle time for each machine [16], which can be regarded as a special type of reconfigurable system where there is only one machine in each stage. The dynamic behavior of the system can be analyzed by using a discrete time Markov Chain (DTMC). The state of the Markov Chain can be represented by the probability distribution of the inventory levels of all the buffers, and the transition between states can be obtained by enumerating the up/down states of all machines [17]. This method is efficient to analyze the system performance when the dimension of state is small. However, when the number of stages increases, the curse of dimensionality arises, which makes the exact analysis intractable. We will analyze the dynamics of a two-stage-one-buffer (2S1B) system in Section 2.2.1, and use it as a building stock to investigate the dynamics of multi-stage systems in Section 2.2.2.

2.2.1 Dynamics for two-stage systems

First, we study a two-stage reconfigurable system, where there are S_1 upstream machines and S_2 downstream machines. Since there is only one buffer, we denote it as B, its capacity as C and its inventory level at (the end of) time k as $N(k)$. Let $\pi_s(k) := \Pr(N(k)=s)$ and $\boldsymbol{\pi}(k) = \begin{bmatrix}\pi_0(k) & \pi_1(k) & \ldots & \pi_C(k)\end{bmatrix}^T$ is the probability distribution of the system states at time k, which satisfies $\|\boldsymbol{\pi}(k)\|_1 = 1$.

Then system dynamic is represented by Equation (1).

$$\boldsymbol{\pi}(k) = \mathbf{P}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)\boldsymbol{\pi}(k-1) \quad (1)$$

where $\mathbf{r}_i^X(k) = [r_i^X(0,k), r_i^X(1,k), ..., r_i^X(S_i,k)]^T$ (X=NA,NB; i=1,2). $\mathbf{P}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)$ is the $(C+1)\times(C+1)$ matrix of the transition probabilities, whose elements can be easily obtained by taking condition on the number of machines that are up in either stage. See [18] for the analytical expression of $\mathbf{P}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)$.

Moreover, in a 2S1B system, the machines in stage 1 are never starved and the machines in stage 2 are never blocked, we have $r_1^{NS}(j,k) = r_1(j,k)$ and $r_2^{NB}(j,k) = r_2(j,k)$, where

$$r_i(j,k) = \begin{cases} \dbinom{S_i}{j} p_i^j (1-p_i)^{S_i - j} & \text{if stage } i \text{ is available at } k \\ \mathbf{I}\{j=0\} & \text{if stage } i \text{ is not available at } k \end{cases} \quad (2)$$

$\mathbf{I}\{X\}$ is an indicator function, representing the true(1)/false(0) value of the statement X.

Similar as Equation (1), the transient production rate (i.e., expected number of parts produced by the last machine) and consumption rate (i.e., the expected number of parts entering the first machine) of the system can also be calculated, as

$$PR(k) = \begin{bmatrix}0 & 1 & \cdots & S_2\end{bmatrix}\mathbf{p}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)\boldsymbol{\pi}(k-1) \quad (3)$$

$$CR(k) = \begin{bmatrix}0 & 1 & \cdots & S_1\end{bmatrix}\mathbf{c}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)\boldsymbol{\pi}(k-1) \quad (4)$$

where $\mathbf{p}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)$ (resp., $\mathbf{c}(\mathbf{r}_1^{NS}(k), \mathbf{r}_2^{NB}(k), C)$) transfers the distribution of buffer levels into the distribution of the number of parts completed by the system (resp., entering the system). Their analytical expression can also be found in [18].

2.2.2 Dynamics for multi-stage systems

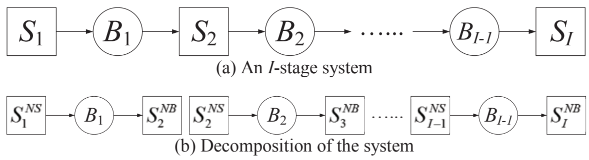

Fig. 3. Decomposition of an I-stage system

We consider the I-stage system in Fig. 2 and simplify it as shown in Fig. 4(a). Similar as the decomposition method in serial line [19], we denote S_i^{NS} and S_i^{NB} as the non-starvation and the non-blockage "dummy" stage S_i, respectively. Then, viewed from buffer B_i ($i=1,...,I-1$), the system can be represented as a two-stage system $S_i^{NS} - B_i - S_{i+1}^{NB}$. Therefore, the entire system can be decomposed into I-1 2S1B subsystems (as shown in Fig. 4(b)), where in these 2S1B systems, $\mathbf{r}_i^{NS}(k)$ and $\mathbf{r}_i^{NB}(k)$ (i = 1,2,…,I) can be calculated by the law of conservation, as shown in Equations (5) and (6).

$$\mathbf{r}_i^{NB}(k) = \mathbf{c}(\mathbf{r}_i(k), \mathbf{r}_{i+1}^{NB}(k), C_i)\boldsymbol{\pi}_i(k-1) \quad (i=1,...,I-1) \quad (5)$$

$$\mathbf{r}_i^{NS}(k) = \mathbf{p}(\mathbf{r}_i(k), C_{i-1})\boldsymbol{\pi}_{i-1}(k-1) \quad (i=2,...,I) \quad (6)$$

A recursive algorithm has been developed in [18] to calculate $\mathbf{r}_i^{NB}(k)$ and $\mathbf{r}_i^{NS}(k)$ for each i=1,…,I. Once they are obtained, the distribution for buffer B_i (i=1,…, $I-1$) can be analysed from Equation (1), as

$$\boldsymbol{\pi}_i(k) = \mathbf{P}(\mathbf{r}_i^{NS}(k), \mathbf{r}_{i+1}^{NB}(k), C)\boldsymbol{\pi}_i(k-1) \quad (i=1,...,I-1) \quad (7)$$

Equations (5) to (7) can be used recursively to update the system dynamics at every time k, and the production rate of the system at time k can be calculated as

$$PR(k) = \begin{bmatrix}0 & 1 & \cdots & S_I\end{bmatrix}\mathbf{p}(\mathbf{r}_{I-1}^{NS}(k), \mathbf{r}_I^{NB}(k), C_{I-1})\boldsymbol{\pi}_{I-1}(k-1) \quad (8)$$

2.3. Process description

A resilient system is designed with redundancy or flexibility that can mitigate the effect of the disruption. As introduced in Section 1, here we consider two policies (policy A and policy B, which will be introduced below) that can be applied when the disruption occurs. Specially, we also denote policy O for the system without such capability (i.e., policy O means no control action during the disruption).

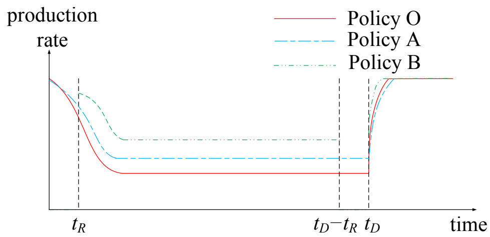

Fig. 4. Evolution of system production rate under different policies

Policy A is to increase the speed of the machines in the stage where the disruption occurs. We assume that the time to change the machine speed is negligible, so the process under policy A can be divided into two periods. Period A1 (k = 1 to t_D) is the duration under the disruption, during which the speed of the machines in stage i_d is increased while that in the other stages does not change. Moreover, Period A2 ($k > t_D$) is the post-disruption period where all the machines are running with the original speed. Policy O can be regarded as a special case of policy A where the increase in speed is 0.

Policy B is to reconfigure the system and to reallocate the tasks among stages. In other words, the stage with fewer machines needs to do fewer tasks, and thus its cycle time will be smaller than the other stages. We assume that the reconfiguration process takes a duration of t_R, and during the reconfiguration periods, parts in the buffers can be adjusted to be ready for the next stage of the new system (the system after reconfiguration). Then the process under policy B can be classified into four periods. Periods B1 (k = 1 to t_R) and B3 ($k = t_D - t_R + 1$ to t_D) are two reconfiguration periods during which the entire system is shut down for reconfiguration and hence there is no throughput. Period B2 ($k = t_R + 1$ to $t_D - t_R$) is the reconfigured system with the reallocated tasks. Period B4 ($k > t_D$) is the transient between the completion of the second reconfiguration and the time when the system runs back to its steady state. In Period B4, the system is back to its original configuration.

Fig. 4 shows the evolution of the system production rate under different policies.

2.4. Resilience measures

The transient production rate of the system under different policies can be evaluated based on the method developed in Section 2.2. Let $PR^P(k)$ denote the production rate at time k under policy P (P=A, B, or O; and hereafter we use the superscript 'P' to represent the corresponding performance under policy P). Then the three throughput-related resilience measures can be calculated based on $PR^P(k)$'s.

The first resilience measure is production loss caused by the disruption. It consists of the production loss during the disruption and that after the disruption. It can be calculated as

$$PL^P = \frac{t_D}{T_I^O(0)} PR^S - \sum_{k=t^P+1}^{t_D - t^P} PR^P(k) + \sum_{k=\frac{t_D}{T_I^O(0)}+1}^{\infty} \left(PR^S - PR^P\left(kT_I^O(0)\right) \right) \quad (9)$$

where $t^P = t_R \cdot \mathbf{I}\{P = B\}$.

The second one, throughput settling time, is the time that the production rate of the system returns to $(1-\varepsilon)$ of its steady-state value, and keeps at least that value afterwards, as

$$TST_\varepsilon^P = \max\left\{ k \middle| k \geq \frac{t_D}{T_I^O(0)}, PR^P(kT_I^O(0)) < (1-\varepsilon)PR^S \right\} T_I^O(0) + T_I^O(0) - t_D \quad (10)$$

The third one, total under production time, measures the total time that the production rate of the system is below $(1-\varepsilon)$ of its steady-state value. It can be calculated as

$$TUT_\varepsilon^P = t_D + \sum_{k=\frac{t_D}{T_I^O(0)}+1}^{\infty} \mathbf{I}\{PR^P(kT_I^O(0)) < (1-\varepsilon)PR^S\} T_I^O(0) - \sum_{k=1}^{\left\lfloor \frac{t_D - 2t^P}{T_I^P(t^P)} \right\rfloor} \mathbf{I}\{PR^P(t^P + kT_I^P(t^P)) \geq (1-\varepsilon)PR^S \cdot \frac{T_I^P(t^P)}{T_I^O(0)}\} T_I^P(t^P) \quad (11)$$

In the following section, a numerical case study will be conducted to further study how the resilience measures are affected by these built-in capabilities.

3. Case study

We consider the design of a system composed of six machines with an identical reliability of 0.95, and a total buffer size of 10. The manufacturing process consists of 30 operations, with each taking 10 seconds. Therefore, the total process time for one part is 300 seconds. Two reconfiguration configurations are used for comparison, as shown in Fig. 5, where configuration (a) is two-stage system whose buffer size is 20, and configuration (b) is a three-stage system with two buffers, each of which has a capacity of 10.

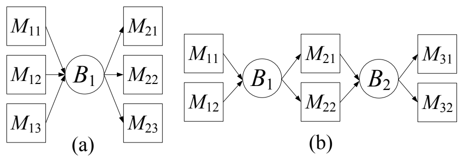

Fig. 5. Configurations of the six-machine systems

It is assumed that under policy A, the cycle time of each machine can be reduced by at most 20%, and under policy B, the system can be fully reconfigured. Table 1 shows the cycle times of the original systems and that of the systems under policies A and B. For example, in the original configuration (a), all machines need to do half of the total tasks, and thus the cycle time is 150 seconds. However, when the system is reconfigured, the stage where the disruption occurs has two machines, and thus it only needs to perform two fifths of the total tasks, indicating a cycle time of 120 seconds. Similar calculation can be applied to configuration (b).

Table 1. Cycle times for machines under different policies

	cycle time of each stage (sec)				
	Pol.O	Pol. A (Period A1)		Pol. B (Period B2)	
	all	w/ dis.	w/o dis	w/ dis.	w/o dis.
(a)	150	120	150	120	180
(b)	100	80	100	60	120

Next, we evaluate the three resilience measures in both configurations, where the disruption may occur in any stage.

3.1. Effect of system configuration, disruption duration, and disruption location

First, we assume that the disruption lasts for one hour (3600 seconds) or two (7200 seconds), and each reconfiguration period is 300 seconds. From Section 2, one can obtain these resilience measures for each configuration, as shown in Table 2, where the unit for each $TST_{0.02}^{P}$ and $TUT_{0.02}^{P}$ is second.

Table 2. Resilience measures under different policies

t_D = 3600 sec					
Resilience Measures	Configuration (a)		Configuration (b)		
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 3
PL^O	19.58	19.58	30.85	31.92	30.85
PL^A	5.48	9.16	18.30	21.59	22.83
PL^B	23.11	15.34	21.30	20.91	19.11
$TST_{0.02}^{O}$	1650	150	3300	1100	100
$TST_{0.02}^{A}$	900	150	3300	1100	100
$TST_{0.02}^{B}$	150	150	100	100	100
$TUT_{0.02}^{O}$	4800	3600	6400	4500	3600
$TUT_{0.02}^{A}$	2700	3600	6100	4300	3600
$TUT_{0.02}^{B}$	3600	3600	3600	3600	3600
t_D = 7200 sec					
Resilience Measures	Configuration (a)		Configuration (b)		
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 3
PL^O	42.19	42.19	64.52	65.59	64.52
PL^A	14.98	20.59	42.52	46.29	48.56
PL^B	34.34	31.58	32.48	31.97	31.04
$TST_{0.02}^{O}$	1650	150	3300	1100	100
$TST_{0.02}^{A}$	1650	150	3300	1100	100
$TST_{0.02}^{B}$	150	150	100	100	100
$TUT_{0.02}^{O}$	8400	7200	10000	8100	7200
$TUT_{0.02}^{A}$	6150	7200	9700	7900	7200
$TUT_{0.02}^{B}$	7200	7200	7200	7200	7200

Table 2 illustrates the following characteristics of the three resilience measures.

PL^O when the disruption occurs in the beginning/end of the system is smaller than that when the disruption occurs in the middle of the system, because the stages in the middle of the system are more easily to be blocked or starved. Moreover, the more stages the system has, the more production loss will be saved by policy B, but the less production loss will be saved by policy A. When the duration of the disruption t_D gets larger, policy B becomes more advantageous, because it rebalances the system to the maximum extent.

TST_{ε}^{O} decreases as i_d increases (i.e., as the location of the disruption is closer to the last stage). The reason is that after the disruption, it will take a shorter time for the production recovery to propagate to the last stage if the disruption is closer to it. In most cases, TST_{ε}^{A} is smaller than TST_{ε}^{O}, and TST_{ε}^{B} equals the system cycle time, indicating an immediate recovery of the system production rate when the disruption ends. Moreover, TST_{ε}^{P} (P=A, B, and O) is relatively independent of t_D.

TUT_{ε}^{O} also decreases as i_d increases. When the disruption occurs in an upstream stage, the buffers in the system can reduce the variation of the system production rate caused by the disruption. In most cases, TUT_{ε}^{B} equals to the duration of the disruption, while in some cases TUT_{ε}^{A} is even smaller than it, indicating that policy A introduces a larger variation on the system production rate. Additionally, TUT_{ε}^{P} (P=A, B, and O) increases as t_D increases.

3.2. Effect of buffer capacity on the scaled marginal production loss

As discussed above, the production loss increases as the duration of disruption increases. In this section, we study the marginal increase of the production loss, and investigate how it is affected by the buffer capacities.

We set the durations of the disruption as t_D = 900n (n = 1,...,10) seconds, and define the scaled marginal production loss under policy P (P=A, B, and O) as $\Delta PL^P(t_D) = (PL^P(t_D) - PL^P(t_D - 900))/PR^S$, where $\Delta PL^P(0) = 0$, and $1/PR^S$ is a scaled parameter to compensate for the difference in the steady-state production rates caused by different buffer capacities.

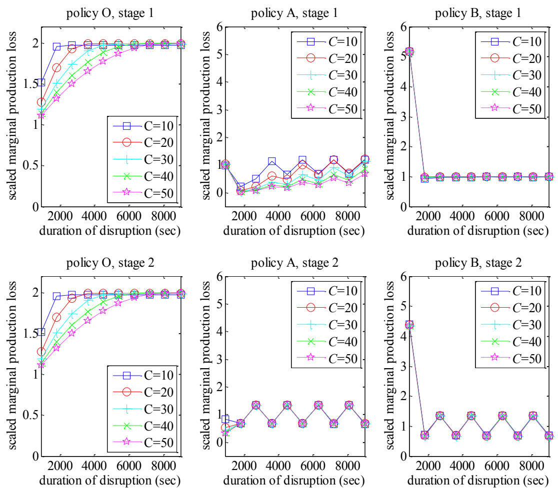

Fig. 6. Scaled marginal production losses with different buffer capacities

We only evaluate the scaled marginal production losses in configuration (a). The machine reliability is still 0.95 and the buffer capacity C varies among 10, 20, 30, 40 and 50. $\Delta PL^P(t_D)$ under different policies are plotted in Fig. 6. It shows that, ΔPL^O converges as the duration of disruption increases. Moreover, under different buffer capacities, the converged ΔPL^O's are similar, while their convergence rates are different. As C gets larger, the convergence rate of ΔPL^O becomes slower, and ΔPL^O becomes smaller under a short disruption. This result indicates that a larger buffer is more capable of mitigating the effect of the disruption, especially when the disruption is short. The pattern of

ΔPL^A also indicates that, under Policy A, the system will have less production loss when the buffer capacity increases. However, ΔPL^B is relatively insensitive with regard to C, because the production loss under Policy B is mainly contributed by the two reconfiguration periods.

3.3. Discussion

From the numerical results in Sections 3.1 and 3.2, we suggest the following observations. (1) The system resilience can be improved by built-in redundancy (i.e., capability of speed increase) and flexibility (i.e., option for system reconfiguration). (2) Reconfiguration is very advantageous when the duration of disruption is long or the system has more stages. (3) The system with more parallel machines is more resilient. (4) Buffers can make the system more resilient (smaller production loss) under short-duration disruptions, especially when the capacities of the buffers are large.

These observations offer insights to the design of manufacturing system for resilience. There are also other factors that need to be considered. For example, a more resilient system is usually more expensive. We should also note that a parallel configuration may increase the variations on the quality of the products. Integrating the resilience analysis in this paper with other techniques, such as prognostics analysis [20] and stream-of-variation analysis [21], one can decide which level of flexibility and redundancy should be built in the system so that the system is both resilient and cost-effective. These decisions include the system configuration, the number and capability of the machines in each stage, and the size of buffers between stages, etc.

4. Conclusion

In this paper, we proposed three important resilience measures for manufacturing systems under disruptions. These three resilience measures – production loss (PL), throughput settling time (TST_ε), and total underproduction time (TUT_ε) – are analyzed by using a Bernoulli reliability model. Two built-in capabilities of the system are considered to mitigate the effect of disruptions. We conduct numerical studies to investigate how the system resilience measures are affected by the system configurations, the built-in system capability, and the buffer capacities. The results show that, the built-in redundancy and flexibility can improve the system resilience performance, especially when the disruption is long, or the system has small number of parallel machines in each stage. For systems without redundancy or flexibility, parallel configurations are more resilient than serial configurations. Moreover, the existence of buffers in the systems can mitigate the impact of the short-duration disruptions, and thus a system with larger buffers is more resilient.

The resilience analysis considering the propagation of unexpected disruptive events and the capability of recovery provide a novel, useful guidance for manufacturing system design. It helps the system designer to determine the optimal level of redundancy and flexibility to be built in the manufacturing systems, in order to make the system both resilient and cost-effective.

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