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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 <i>available</i> at the beginning of time $k$
$r_i^{NS}(j,k)$	the probability that there are $j$ machines in stage $i$ that are <i>available and not starved</i> at the beginning of time $k$
$r_i^{NB}(j,k)$	the probability that there are $j$ machines in stage $i$ that are <i>available and not blocked</i> 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

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 ( $TST_e$ )* and *total underproduction time ( $TUT_e$ )*. When disruption occurs, a resilient system should have smaller values of these three measures than a system that is not resilient.

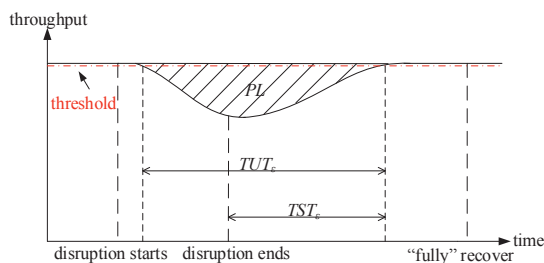


Fig. 1. Disruption profile and resilience measures

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:

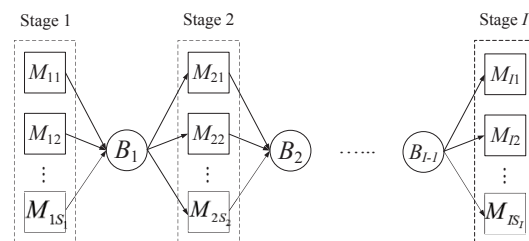


Fig. 2. An  $I$ -stage system

- 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

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