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Technical Paper

Allocation of maintenance resources in mixed model assembly systems

Weihong Guo[a,*], Jionghua (Judy) Jin[a], S. Jack Hu[a,b]

[a] Department of Industrial and Operations Engineering, The University of Michigan, Ann Arbor, MI 48105, USA
[b] Department of Mechanical Engineering, The University of Michigan, Ann Arbor, MI 48105, USA

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ABSTRACT

Mixed-model assembly systems (MMASs) have been well recognized for their ability to handle product variety for mass customization. With multiple products to produce, the prioritization of maintenance work-order becomes more crucial and challenging. This paper develops a quantitative method to systematically determine maintenance work-order priorities in an MMAS using on-line production information. The effect of product mix ratio on maintenance decisions is studied in detail. Based on the proposed approach, one can search for an optimal maintenance plan that will lead to improved productivity within the optimization horizon.

1. Introduction

In today's marketplace, where customers demand high product variety and short lead time, manufacturing systems have evolved from the traditional dedicated assembly lines where only one product model was produced in large quantities to today's mixed-model assembly systems (MMASs). MMASs have been well recognized for their ability to handle increased variety resulting from mass customization.

An MMAS typically consists of common operation stations and variant operation stations. The stations for common operations process assembly tasks that are common to all types of products, while the variant stations are used to perform different tasks required for individual product types. In this way, a variety of products can be produced in an MMAS. Although MMASs can provide better flexibility to meet customer demands with short production lead time, system configurations of an MMAS become highly complex. Moreover, since the product values for various parts are different and the production routes for each product can vary significantly in an MMAS, the product variety and their demand ratio will significantly affect the priorities of executing maintenance work-orders, especially when there are more maintenance work-orders than available people or resources. Therefore, the prioritization of maintenance work-order becomes crucial and challenging in an MMAS.

Although there exists lots of research in the literature in addressing the problem of maintenance prioritization, most practical approaches rely on expert experience and knowledge, intuitions, or trial and errors. There has been limited research in developing quantitative prioritization methods that can be effectively applied to MMASs. There exists a need to develop a quantitative method to systematically determine maintenance work-order priorities in an MMAS with the integration of on-line production information (e.g., station failure status and buffer contents), which is the focus of this paper. Specifically, this paper extends the existing system value method [1] to an MMAS for assigning priorities to the maintenance work-orders using on-line information. For this purpose, the effect of the mix ratio between different product variants on the maintenance decisions will also be studied in detail. Based on the proposed approach, one can search for an optimal maintenance resources allocation plan that will lead to improved productivity within the optimization horizon.

1.1. Literature review

The topic of maintenance resources allocation has been widely studied in recent decades and the importance of maintenance prioritization has been well recognized [2,3]. The commonly used prioritization methods include the use of heuristic rules or common sense derived from human expert knowledge. Triantaphyllou et al. [4] and Vanier et al. [5] provide comprehensive reviews of important criteria used in the existing maintenance decision models for prioritizing maintenance alternatives. In Moazami et al. [6], the Analytic Hierarchy Process was used to facilitate the prioritization of alternatives in pavement maintenance. In this method, the dependency relationships among various decision factors are considered rather than treating those factors individually. All work-order criteria are quantitatively rated based on

* Corresponding author. Tel.: +1 734 730 5978.
E-mail addresses: graceguo@umich.edu, darlingguoguo@gmail.com (W. Guo).

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Table 1
Simulation conditions for Models A1, A2, A3, and A4.

Machine center	Downtime frequency	Repair times (min)			
		Model A1	Model A2	Model A3	Model A4
S_4	P(30), decision time: 5 min	9	exp(9)	12	exp(12)
S_7		9	exp(9)	12	exp(12)

their relative preference over each other, which can be either objective or subjective. Reliability indices are also commonly used to determine maintenance prioritization. Li et al. [7] presents a weighted average system reliability index (WASRI) subject to the cost constraints, in which the weights and reliability indices can be highly subjective. In Hathout et al. [8], the priority risk indices (PRIs) are introduced to handle maintenance prioritization in transmission lines. The PRIs consist of the product failure probability, line condition function, and failure consequences function. Both the line condition function and failure consequence are categorical variables that are determined by common sense or human expert knowledge. Most current industrial practice indicates that the majority of priority assignments of maintenance work-orders are often done subjectively according to the experience and knowledge of the maintenance coordinator. Due to inevitable randomness in both the production system and maintenance system, it is impossible to completely avoid the conflicts between the required work and available resources. Therefore, a quantitative method is needed to systematically assign priorities to work-orders in order to minimize the influence of these conflicts. Moreover, in today's industries, the production and assembly systems become very complex due to high product variety and customer demand; this makes human judgment and heuristic rules less effective in maintenance prioritization. Additionally, the manufacturing systems and processes may also evolve very fast to produce various new products, which make expert experience and knowledge very limited and insufficient for subjective decision-making. Therefore, an effective quantitative measure is needed to evaluate the system performance and prioritize maintenance work-orders Table 1.

The system throughput has been widely used to quantitatively measure the performance of a system's maintenance prioritization. Throughput can be directly used to evaluate the average performance of the production system; however, the maintenance work-orders are more sensitive to real-time production information than the average system performance. Moreover, the dynamic status of a production system needs to be considered in the maintenance priority assignment since the machines are operated in a highly dynamic manner that varies over time. The importance of the on-line information, including the machine status and the production flow, has already been stressed in Koc et al. [9]. Such information can be used to enable a more efficient and cost-effective maintenance decision making [1,10,11]. To capture the real-time production information, the buffer contents are very important for maintenance decision making because the finite buffer capacity makes it crucial to prioritize maintenance works in order to achieve a balanced workflow and high profit. Recently, a *system value* approach was proposed [1] for maintenance prioritization with the incorporation of online production information including buffer contents.

There have been extensive studies on the design of MMAS process [12,13], modelling of the complexity and performance of MMASs [14,15], and balancing of production lines in MMASs [16,17], etc. However, there is little study on the maintenance prioritization decision or reliability analysis for MMASs. The focus of this paper is to integrate the on-line production information (e.g. station failure status and buffer contents) into the maintenance work-order prioritization for MMASs.

1.2. Review of system value method

Intuitively, the performance of any production system can be directly expressed as the total amount of value that has been added during a certain production period. The total value added consists of finished products as throughput and unfinished work-in process at the current instant. These intermediate parts in the system also have contributions to the overall system throughput later on. The value of a part, called part value, varies with the changes in system layout and the part's location in the system. The "no shut off" rule [18] assumes that when one machine in the system fails, all other working machines will continue to process the parts until they are either blocked or starved. Therefore, even during the downtime of a machine in the system, work can still be performed on some intermediate parts and values can be added to them.

The system value is defined as the summation of all part values existing in the system at a given moment t. For a simple production system with a single product type being produced, the system value [9] at a given time t is mathematically defined as

$$W(t) = \sum_{i=1}^{n} v_i C_i(t) \tag{1}$$

where n is the number of stations in the system, $C_i(t)$ is the number of parts held in station i, and v_i is the part value for a part in station i. The system value defined in Eq. (1) represents the work done by the production system on the parts existing in this system (including the raw parts, finished products, and work-in-progress). Although this approach can quantitatively evaluate the effects of different alternatives with the consideration of on-line production information, it was established to handle the maintenance prioritization in systems that produce only one product type and could not be directly applied to MMASs. We need a quantitative measure to effectively consider the multiple product types and their different values in the system in order to make an effective maintenance prioritization decision for MMASs.

1.3. Paper organization

The remainder of the paper is organized as follows: Section 2 extends the system value method for assigning priority to maintenance work-orders for MMASs. In Section 3, maintenance decision making for an example assembly system with a series of predefined downtime scenarios is carried out via simulations. The priority effects are evaluated and the simulation results are analyzed in detail. Further discussions on the advantages of the system value method over the total throughput method are presented in Section 4, where the determination of sample size is also addressed. Finally, Section 5 states the main conclusions and directions for future work.

2. Methodology

2.1. System value index for MMASs

A quantitative measure for describing the effects of any given maintenance priority decision in an MMAS is defined in this section. The system value approach reviewed in Section 1.2 is extended

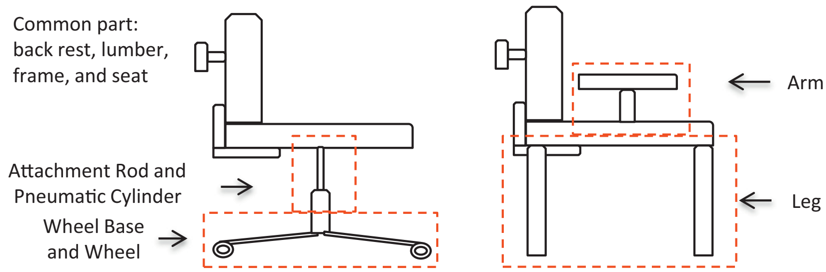

Fig. 1. Modules of two types of chairs.

to multiple product types for an MMAS, which will be used as a performance index in determining maintenance work-order priorities.

For an MMAS with multiple product types, some machines will operate on more than one type of parts and their corresponding buffers will store multiple types of parts. Since the various parts may have different values by passing through different routes, a different set of part values should be used for each product type in the system. Therefore, the extended definition of the system value for an MMAS can be expressed as

$$W(t) = \sum_{i=1}^{n}\sum_{j=1}^{m}(v_{i,j}C_{i,j}(t)) \quad (2)$$

where $W(t)$ is the summation of all part values existing in the system at a given time t, n is the number of stations in the system, m is the number of part types the system is capable to produce, $v_{i,j}$ is the part value of part type j at station i, and $C_{i,j}(t)$ is the buffer content level of part type j at station i at time t.

To consider the different profits made by different products that are produced in the system, w_j is defined by part j's unit price p_j minus its unit cost c_j, i.e., $w_j = p_j - c_j$, to describe part j's contribution to overall system profit. The part value $v_{i,j}$ represents the accumulative value added to part j up to station i when it passes through its quickest production path from the beginning of the production process. Therefore, when a part j is currently at station i, $v_{i,j}$ is a percentage of w_j since the part j is an unfinished part at station i. This percentage describes part j's completeness during its production in the system, with "1" indicating a finished part and a "0" indicating a raw part. Therefore, the product completeness at station i can be defined as the ratio of the total cycle time of machines on part j's production path till station i to the total cycle time of all machines on part j's production path. Part j's completeness is increased along the production flow and will reach maximum 100% at the end of the production system. Therefore, the part value $v_{i,j}$ at any station i can be generally expressed as

$$v_{i,j} = \frac{\sum_{k=1}^{i} T_{k,j}}{\sum\limits_{\text{all } k\text{'s on } j\text{'s production path}} T_{k,j}} \times w_j \quad (3)$$

where $T_{k,j}$ is the cycle time of machine k on part j's production path. Now, the part value at any station in an MMAS is defined and computed for a given point in time t. When the real-time content level of any part type at any station is obtained, the total system value $W(t)$ can be calculated and serve as a quantitative measure of the dynamic system status at any given time t. Further discussion on the advantages of using the defined system value index over the conventional total throughput index will be presented in Section 4.

2.2. Evaluation of priority effects

Based on the system value index introduced in Eqs. (2) and (3), $W(t) - W(0)$ describes the total system value created in an MMAS from the beginning of production till time t. For an MMAS during a certain production period $[t_0, t_0 + T]$, the efficiency of maintenance works can be quantitatively measured by $W(t_0 + T) - W(t_0)$. A higher value of $W(t_0 + T) - W(t_0)$ indicates that such a maintenance priority creates more value and thus should be preferred. Hence, the optimal maintenance prioritization strategy can be determined by searching for the scenario when the maximum value of $W(t_0 + T) - W(t_0)$ is achieved.

Since $W(t_0 + T) - W(t_0)$ is significantly affected by not only the priority effects, but also system configuration and its downtime scenarios, an analytical evaluation of priority effects is difficult to achieve; hence, computer simulations are used to perform the evaluation in this study. For a predefined simulation time length S, all system statuses are collected between the starting time Ts and the ending time $Te = Ts + S$. The system statues are then transformed into the system value format using the methods described in Section 2.1 and yielding system values: $W(Ts)$ and $W(Te)$. The difference expressed as $V = W(Te) - W(Ts)$ describing the value created during the time period $[Ts, Te]$, is then a quantitative measure representing the effects of a given maintenance order priority. In this work, we used ProModel [19] to realize such discrete-event simulations to track the part flow and collect data.

With sample size N, the output is a vector $\boldsymbol{V}$ instead of a single value. The vector $\boldsymbol{V}$ is used to determine the most profitable maintenance priority in optimization by exploring its average value, confidence interval, and distribution. Generally, a larger sample size is preferred in order to reduce variation, but the computing time may also be costly for a real time implementation. The possibility of reducing sample size will be discussed in Section 4.

2.3. Demonstration of methodology

In this section, simulation experiments with some simple scenarios are carried out in order to demonstrate the methodology addressed above and discover the importance of mix ratio on the maintenance priority in MMASs. More detailed analyses will also be addressed with a case study in Section 3.

To explore the effects of different maintenance priorities through simulation, an MMAS is established for producing two types of chairs. As shown in Fig. 1, chairs A (wheeled chairs) and B (no-wheel chairs) are produced in an assembly system with a mix ratio p = A:B. Both types of chairs have back rest, lumber, frame and seat as common components, while the dashed boxes in Fig. 1 show the variant components in the two types of chairs.

Fig. 2 shows the assembly system to produce chair A and chair B. Machines S_1 and S_2 provide common operations for assembling back rest, lumbar, frame and seat, and S_{21} and S_{22} are parallel machines needed for production line balancing for S_2. S_4 and S_5 provide variant operations for assembling the rod, pneumatic cylinder, wheel base, and wheel for chair A; S_6 and S_7 provide variant operations for assembling the arms and legs for chair B. When a component comes into the system, it goes through S_1 and S_2 (either S_{21} or S_{22}), then the intermediate part of Type A goes to S_4 and S_5,

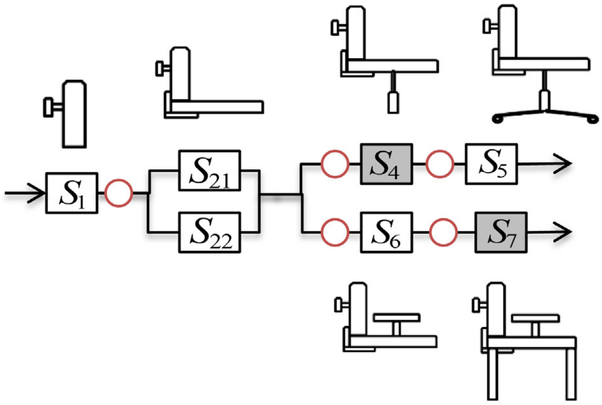

Fig. 2. Configuration of an assembly system.

and the intermediate part of Type B goes to S_6 and S_7, respectively. The mix ratio p, which indicates the workload for Type A and Type B, is an important parameter affecting maintenance priority decision.

To explore the significance of the mix ratio, a set of mix ratio values including 2:8, 3:7, 4:6, 5:5, 6:4, 7:3, and 8:2 are studied (i.e., The Product A's percentage is equal to 0.2, . . ., 0.8, respectively).

The following is assumed in simulation:

- Inter-arrival times of starting parts are independent and identically distributed (i.i.d.) random variables that follow a Poisson distribution.
- There is a finite buffer with the capacity of 50 units located between any two consecutive machines. The incoming queue serves as an infinite buffer and the initial buffer content is zero for all buffers.
- Machine processing times are i.i.d. random variables that follow a Poisson distribution with the cycle time of 3 min.
- Each product type has a unit price and a unit cost. To start with a simple simulation case, assume products A and B to have the same selling price, and the same unit cost.

To illustrate the impact of mix ratio, assume S_4 and S_7 suffer machine failures at almost the same time and follow the same distribution, while all other machines have no failures. One maintenance personnel is in the plant to perform all the repairs and maintenance. S/he starts working on a failed machine immediately after the failure occurs, and s/he can only work on one machine at a time. An operator "→" is defined to describe the sequence of maintenance work-orders. $S_4 \rightarrow S_7$ indicates the maintenance personnel works on S_4 first and then on S_7.

In simulation, we choose the production length to be almost one work shift, e.g., S = 8 hours, since the maintenance decision-making is usually a short term decision process. Ts = 300 min is used as a warm-up period, and sample size N = 500. We experimented with a case that S_4 and S_7 suffer machine failures every 30 min, and the repair of each machine takes 9 min (denoted as model A), and the results are shown in Fig. 3, including average system value and 95% confidence intervals. Given a certain mix ratio, the maintenance priority leading to a higher value should be preferred since it indicates a more effective system.

Intuitively, maintenance work should be performed on S_7 first if we have a lot more demands for Product B than Product A. This intuition is confirmed in Fig. 3, i.e., when the mix ratio goes towards the extreme case of 2:8, it is more desirable to have the $S_7 \rightarrow S_4$ strategy to generate a higher system value. The same conclusion is held for the mix ratio of 8:2 when more products of Type A are to be produced than that of Type B.

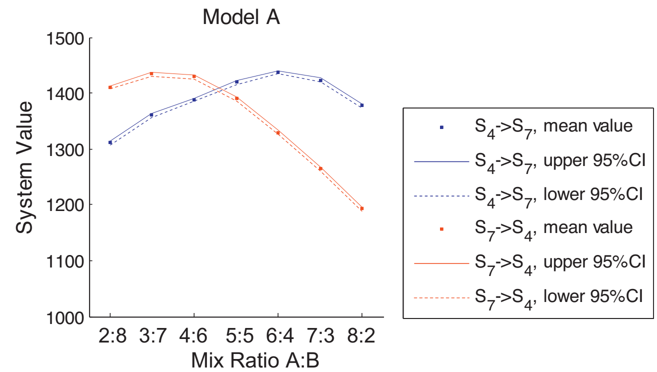

Fig. 3. Average system value and 95% confidence intervals from model A.

Fig. 3 also shows the decreasing trend caused by the finite buffer and machine blockage during production as the mix ratio moves towards the two extreme cases, 2:8 and 8:2. Furthermore, Fig. 3 shows a narrow intersection where maintenance priority has little influence on the system value. Therefore, this range of the mix ratio serves as the decision threshold for switching the maintenance priority between S_7 and S_4. The location of the maximum average system value, the slopes of the increasing and decreasing trends, and the intersection may all vary with different downtime scenarios and system configurations.

Given a system configuration and its downtime scenario, the presented methodology can quantitatively measure the efficiency of maintenance works and determine work-order priorities accordingly under various product mix ratios, which will be addressed in detail with a case study in the next section.

3. Case study

In this section, we will explore the effect of the product mix ratio on the decision threshold with a more realistic scenario, which assumes S_4 and S_7 to have identical random failure arrival rates following a Poisson distribution. It is also assumed that the maintenance person needs 5 min of preparation after he receives a failure signal. Therefore, if S_4 and S_7 both fail within the 5 min preparation time, the maintenance person needs to decide a priority for the work-orders. Otherwise, he just simply follows the first-come-first-serve strategy.

3.1. Simulation scenarios

The same system configuration as shown Fig. 2 is used in the simulations. Assumptions of production time, part arrival rate, and buffer capacity remain the same. Four experimental scenarios are carried out in simulation with different repair times used in each scenario (denoted as model A1, A2, A3, and A4). In these scenarios, the repair times for S_4 and S_7 are set to be deterministic 9 min, deterministic 12 min, exponentially distributed exp(9), and exp(12), respectively.

3.2. Simulation results

Figs. 4–7 show the simulation results of the average system value and its 95% confidence interval for Models A1–A4 respectively with 500 replications in the simulations.

The effect of the mix ratio is reflected by the curve trends, location of the peak points, slope of the step-wise lines, and the location and width of the intersection. Furthermore, by comparing the results of Model A1 and A2 (or Model A3 and A4), it shows how the repair time distribution affects the effect of the mix ratio on

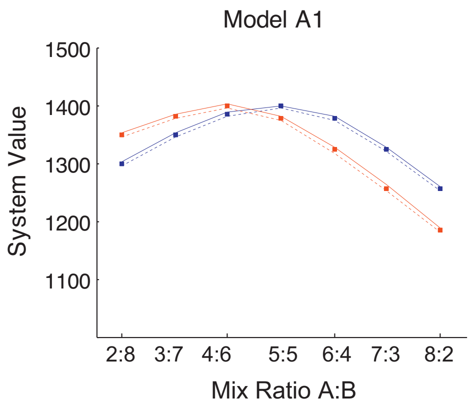

Fig. 4. Average system value and 95% confidence intervals from Model A1, repair time = 9 min.

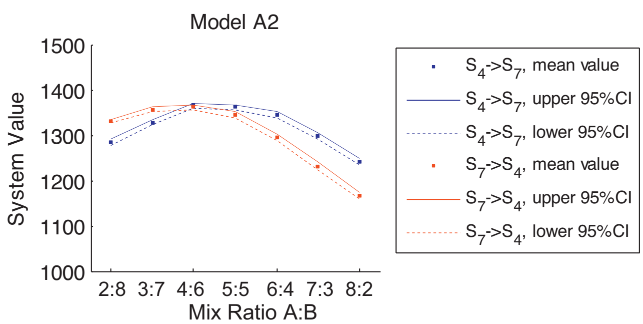

Fig. 5. Average system value and 95% confidence intervals from Model A2, repair time = exp(9).

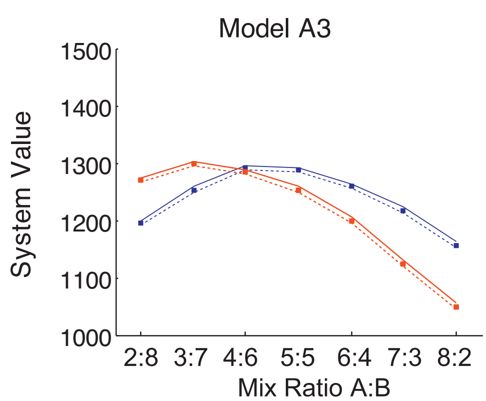

Fig. 6. Average system value and 95% confidence intervals from Model A3, repair time = 12 min.

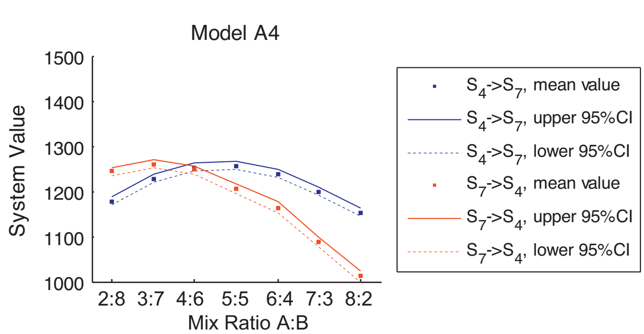

Fig. 7. Average system value and 95% confidence intervals from Model A4, repair time = exp(12).

the maintenance action. By comparing the results of Model A1 and A3 (or Model A2 and A4), it can further indicate how the length of repair times affects the effect of the mix ratio on the maintenance action.

Optimal product mix ratio

Figs. 4–7 show that when the mix ratio goes towards the extreme case of 2:8, it is more desirable to have the $S_7 \rightarrow S_4$ strategy leading to a much higher average system value, i.e., maintenance work should be performed on S_7 first if we have a lot requiring more Product B than product A. Similarly, the $S_4 \rightarrow S_7$ strategy achieves a higher average system value when the mix ratio is between 5:5 and 8:2 with more Product A than Product B to produce. The system value decreases from the peak value as the mix ratio varies towards both ends 2:8 and 8:2. The decreasing trend is caused by a finite buffer and machine blockage during production.

Interaction between downtime and peak position

Figs. 4–7 show that the value of the mix ratio leading to the maximum system value varies at different downtime scenarios and system configurations. Comparing the peak positions in Figs. 4–6, or Figs. 5–7, it can be seen that $S_7 \rightarrow S_4$ has its peak position shifted from mix ratio 4:6 to 3:7 when repair times are increased. In the $S_7 \rightarrow S_4$ strategy, longer repair times cause more A to be blocked and thus push the peak position to shift to a mix ratio level with fewer A to produce. It is noted that the peak positions for $S_4 \rightarrow S_7$ also have a tendency to shift to a lower A mix ratio when repair times are increased, although the tendency is shadowed by the large variances when comparing Figs. 5–7.

Sensitivity of the product mix ratio on system value

In Figs. 4–7, the slope of increase/decrease represents how significant the mix ratio affects the production performance in terms of the system value. With a steeper slope, the mix ratio plays a more important role in affecting the system performance. Comparing Figs. 4–6 where the latter comes from a scenario with longer repair times, repair times affect the system performance in both the average system values and confidence intervals by directly affecting buffer contents and machine blockage time. With a longer repair time, the slope becomes steeper, which indicates that the changes in the product mix ratio lead to larger differences in system performance. Hence, the longer repair times we have, the more important the mix ratio becomes. Correspondingly, with very short repair times (responsive repairs), the mix ratio becomes less important.

Decision robustness of maintenance priority

It is noted that two maintenance strategies intersect when the mix ratio falls into a certain range within the confidence interval. This intersection is a region, narrow or wide, instead of a single point due to the randomness in the system, such as arrival time, processing time, etc. At the intersection, there is not much difference on the system value generated by different maintenance priorities. Therefore, the intersection region and its mix ratio range can reflect the robustness of the maintenance decision-making process. Comparing the intersections in Fig.s 4–6, or Figs. 5–7, it can be seen that there is a shift for the intersection when the repair time is increased. Comparing the intersections in Figs. 4 and 5, where the latter comes from scenarios with exponential random repair times, the confidence intervals become wider since the exponentially distributed random repair time brought larger variances than the deterministic repair time. Correspondingly, the intersection in Fig. 5 is much wider than that in Fig. 4, indicating that a wider mix ratio range is covered in the intersection with a more robust decision region. The same conclusion can be made by comparing Figs. 6 and 7 as well. Therefore, it should be noted that the location and width of the intersection between maintenance strategies $S_4 \rightarrow S_7$ and $S_7 \rightarrow S_4$ directly affect our decision of choosing a maintenance priority in the most efficient manner. When the mix ratio falls into this region of intersection, it is of little importance to determine which maintenance priority is better. From the above figures, we conclude that with different system configurations, parameters, and downtime scenarios, the intersection may shift and its width may vary. Not only the location and width of the intersection are very important, the shifting of the intersection is also very important.

Summary of results

As shown in Figs. 4–7, when the optimal product mix ratio is between 5:5 and 8:2, the $S_4 \rightarrow S_7$ maintenance strategy is preferred for all models A1, A2, A3, and A4 since it generates the maximum average system value; while the $S_7 \rightarrow S_4$ strategy shows that the maximum system value occurs when the mix ratio is between 2:8 and 5:5. We also conclude that when the mix ratio goes towards 2:8, it is more desirable to have the $S_7 \rightarrow S_4$ strategy, and vice versa. As the repair times increase, the peak positions may shift and the mix ratio plays a more important role in affecting the system performance, and the intersection between the two strategies is also affected. It is also concluded that different distributions of repair times do not affect the average system values or their curve shapes. However, exponential repair times result in larger variances than the deterministic repair time scenarios, and wider intersection.

4. Discussion

4.1. System value vs. throughput

In this section, a case study is used to illustrate the advantages of the proposed system value criterion over the conventional throughput measure. We also discuss the possibility of reducing the simulation sample size based on the satisfaction of the statistical analysis results.

The criterion of system throughput, i.e., the number of finished work-pieces coming out of a production system per unit of production time, has been traditionally used to quantitatively evaluate the effectiveness of a production system. In contrast, this paper extended the concept of system value as a new performance measure to assess the effectiveness of the maintenance priority decisions for MMASs. A direct advantage of the system value criterion is that it considers the values of not only the finished parts, but also the partially processed or finished work-pieces in the production system since they have the values contributing to the overall system throughput eventually. When certain actions (including maintenance) are performed to add the value to the part, the part value should change correspondingly and the previous work will or will not have to be performed again in the remaining work. For the scenario described in Model A, we compared the performance in terms of both system value and throughput. Since products A and B are assumed to have the same price and cost, we use the total throughput (the sum of throughput A and throughput B) to compare with the system value. The results are shown in the figures below.

Both Figs. 8 and 9 have the decreasing curve trends towards the ends of 2:8 and 8:2 correspondingly, which is caused by full buffer content and machine blockage. Therefore, both criteria show similar overall trends.

Two points from the curves of Figs. 8 and 9 are studied closely: P1, if the mix ratio is 2:8, then the priority of $S_4 \rightarrow S_7$ is assigned; P2, if the mix ratio is 8:2, then the priority of $S_7 \rightarrow S_4$ is assigned. Fig. 8 shows that point P1 has a higher system value than point P2. At point P2, many units of type A are produced, but S_4 is always repaired at last. This results in a very low system value. In contrast, at point P1, many type B units are produced, and S_7 is repaired at last, which leads to a large quantity of unfinished Type B parts blocked in the system while waiting for S_7 to be repaired. During the waiting time, the unfinished parts can stay in the buffers either before or after S_6. In other words, S_6 can still add the values to these unfinished parts while S_7 is down. This results in a higher system

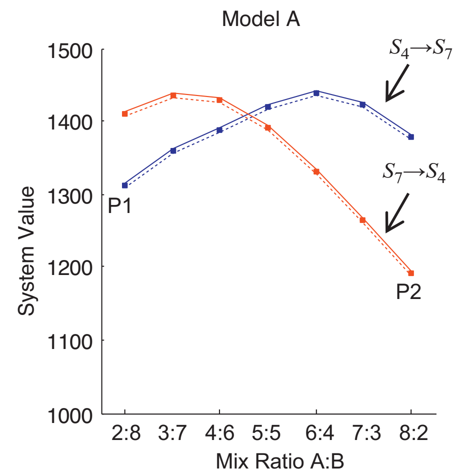

Fig. 8. Average system value and 95% confidence intervals from model A.

value than that at point P2. Therefore, the difference in system values of points P1 and P2 is caused by the different locations of S_4 and S_7 in each of its production lines for part A or part B. Also, the intersection occurs when the mix ratio is somewhere between 4:6 and 5:5 instead of at the exact central point of 5:5. However, Fig. 9 shows that points P1 and P2 have a similar total throughput, indicating they have almost the same production performance. The criterion of the total throughput overlooks the values incurred by the unfinished work-pieces within the system. Due to the location of machines and their downtimes, the number of unfinished work-pieces and their locations in the system may vary in a huge range. This study shows that if we make maintenance priority decisions only based on the total throughput, these important factors may fail to be taken into consideration, thus leading to the risk of making a false priority assignment decision. Therefore, the criterion of system value is suggested for quantitatively assessing the effects of maintenance priorities.

4.2. Sample size analysis

A sample size of $N = 500$ is used in the simulations discussed in the previous sections. A large number of simulation replications (i.e., a large sample size) helps make the variance of the simulation results to be smaller and the average system value to be more accurate. However, a large sample size may be limited for real time decision in some real world applications. The minimal sample size

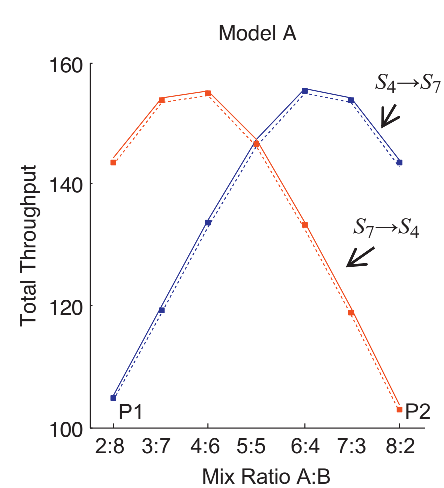

Fig. 9. Average total throughput and 95% confidence intervals from model A.

should be properly determined based on the required simulation performance.

Based on the results from goodness of fit tests [20,21], the Weibull distribution proved to be the best fitted probability distribution of the system values regardless of their downtime scenarios. The shape parameter of Weibull distribution for model A1, A2, A3, and A4 is estimated to vary from 3 to 15 as the mix ratio and maintenance strategy vary. Based on such range of the shape parameter, [22] gives the sufficient sample size to be 132 in order to achieve a Type I error rate of 5%. Hence, we are comfortable reducing the sample size in simulation to around 150. This will provide great convenience when simulation time is a concern for real time implementation.

5. Conclusion

In this paper, the system value method for assigning priority to maintenance work-orders using on-line production information is extended to account for mixed model production and serves as a base for evaluation of maintenance priorities. Then an example assembly system with a set of predefined downtime scenarios is carried out via simulations. The priority effects are evaluated and the simulation results are analyzed in detail. It is also shown that utilizing on-line production information to support maintenance decisions through the system value method provides us much insight into the complex mixed model systems.

The intersection between the performances of different maintenance priorities, caused by randomness in the whole system, directly affects our ability to make clear decisions on maintenance work-orders. The location and width of the intersection are affected by many factors, including system configuration and downtime scenarios. This leads to our future research work on defining the decision thresholds for mixed model systems to help us determine maintenance priority assignment. The proposed method will also be scaled up to apply to problems from larger assembly areas.

Another direction for future work is to extend the concept of system value presented in this paper to take customer demand into consideration. With this extension, system value will not only express the values added by the assembly process, but also how demand is met and the penalty cost or holding cost associated with that, which will help us better prioritize the maintenance work-orders in practice. Another open issue worth investigating is how to address the first-come-first-serve strategy vs. maintenance priority in a more realistic manner. In this paper, we assume there is a decision time delay to perform maintenance work-orders. In practice, when failures occur one after another, the first-come-first-serve strategy should first be applied, otherwise, the assignment of maintenance priorities would be taken into consideration. The maintenance actions will not only be based on priorities, but also depending on the amount of repair work done and the amount left to be done. The maintenance work-order prioritization problem will be more complex when considering the dependence among those decision making factors.

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Weihong Guo received her B.S. degree from Tsinghua University, Beijing, China, in 2010, and the M.S. degree from the University of Michigan, Ann Arbor, in 2012. She is currently a Ph.D. Pre-candidate in Industrial and Operations Engineering at the University of Michigan. Her research interests are in statistical process control, assembly systems, and maintenance strategies. She has presented in professional conferences and published papers in refereed journals/proceedings.

Jionghua (Judy) Jin is a Professor in the Department of Industrial and Operations Engineering at the University of Michigan. She received her Ph.D. degree from the University of Michigan in 1999. Her research focuses on data fusion in system informatics and quality and reliability engineering. She received a number of awards for her work, including CAREER Award in 2002 and PECASE Award in 2004 both from the National Science Foundation, and nine Best Paper Awards during 2000–2012. She is a member of ASME, ASQC, IEEE, IIE, INFORMS and SME.

S. Jack Hu received the B.S. degree from Tianjin University, Tianjin, China, in 1983, and the M.S. and Ph.D. degrees from the University of Michigan, Ann Arbor, in 1986 and 1990, respectively. He is currently a Professor of Mechanical Engineering and of Industrial and Operations Engineering. He conducts research and teaches courses in assembly, manufacturing systems, and statistical methods. He has published more than 200 papers in refereed journals of professional conferences. Dr. Hu is a Fellow of the American Society of Mechanical Engineers (ASME) and a Fellow of the International Academy for Production Engineering (CIRP).