Competing Failure Modeling for Performance Analysis of Automated Manufacturing Systems With Serial Structures and Imperfect Quality Inspection

Zhenggeng Ye, *Student Member, IEEE*, Zhiqiang Cai, *Member, IEEE*, Shubin Si, *Senior Member, IEEE*, Shuai Zhang, and Hui Yang, *Senior Member, IEEE*

***Abstract*—Fierce global competition drives automated manufacturing systems (AMSs) to be increasingly complex, which poses significant challenges on performance analysis and production control. The multistage production via serial stations will lead to the propagation of failures in AMSs, which will affect system performance by triggering complex competitions among multiple failure modes. Although machine performance and product quality have been considered, very little has been done to investigate the effect of imperfect quality inspection on competing failures. Focusing on a time balance serial AMS, this article presents a new competing failure model to investigate the complex interactions among machine failures, product quality, and inspection process, which enables the characterizations of time-delayed propagation of failure, accumulation of degradation, and dynamics of states in serial AMSs. In order to further analyze the impact of competing behaviors on system performance, we have also developed decision diagram models and algorithms, which are evaluated and validated on serial AMSs with imperfect inspection, revealing the characteristic of multistate interactions. Experimental results show that the proposed methods have strong potentials for performance modeling and analysis of serial AMSs and also demonstrate general applicability for manufacturing decision making.**

***Index Terms*—Accumulated degradation, automated manufacturing system (AMS), competing failure, decision diagram, failure propagation, reliability, system dynamics.**

I. Introduction

Automated manufacturing systems (AMSs), as an important type of discrete event systems, have been commonly used by modern industry to gain competitive advantages in fierce global competition [1]. In the design of an AMS, supervisory control and performance analysis are two fundamental research domains. Applications of industrial sensors and actuators greatly improved the supervisory control of AMSs, which were modeled as the cyber-physical system [2]–[7]. However, variety of orders and degradation of machines in AMSs make the performance evaluation intractable. Furthermore, interactions, cooperations, and competitions among machines, products, and inpsections also bring significant challenges to the system-level performance analysis [8].

Competing failure analysis, as one important method to evaluate the performance of complex systems, has been widely used in engineering. It is commonly considered to have two modes in reliability engineering, the competition among multiple degradation processes, and the competition between failure isolation and propagation effects in the time domain. In the former type, the overall degradation process can be divided into continuous degradation caused by static factors and discrete degradation caused by shock [9]–[14]. In the second type, a vast majority of studies addressed issues about failure isolation, effects of failure propagation, and functional dependence [15]–[17]. Despite significant progress in the state of the art, these two competing failures were usually studied separately, which are less concerned about complex interactive behaviors in AMSs with serial stations. In fact, the failure of AMSs with serial stations can be regarded as a dynamic process, which is caused by interactions of multiple competing failure modes [18], [19]. Performance analysis of manufacturing systems has been attempted; however, little has been done to capture the complex

Manuscript received September 10, 2019; revised December 6, 2019; accepted January 2, 2020. Date of publication January 16, 2020; date of current version June 22, 2020. This work was supported in part by the National Natural Science Foundation of China under Grant 71871181, Grant 71631001, and Grant 71771186, in part by the 111 Project under Grant B13044, and in part by the Innovation Foundation for Doctor Dissertation of Northwestern Polytechnical University. Paper no. TII-19-4177. *(Corresponding author: Zhiqiang Cai.)*

Z. Ye is with the School of Mechanical Engineering and the Ministry of Industry and Information Technology Key Laboratory of Industrial Engineering and Intelligent Manufacturing, Northwestern Polytechnical University, Xi'an 710072, China, and also with the Complex Systems Monitoring Modeling and Control Laboratory, Harold and Inge Marcus Department of Industrial and Manufacturing Engineering, Pennsylvania State University, University Park, State College, PA 16802-1401 USA (e-mail: yezhenggeng@outlook.com).

Z. Cai, S. Si, and S. Zhang are with the School of Mechanical Engineering and the Ministry of Industry and Information Technology Key Laboratory of Industrial Engineering and Intelligent Manufacturing, Northwestern Polytechnical University, Xi'an 710072, China (e-mail: caizhiqiang@nwpu.edu.cn; sisb@nwpu.edu.cn; zhangshuai 5000@nwpu.edu.cn).

H. Yang is with the Harold and Inge Marcus Department of Industrial and Manufacturing Engineering, Pennsylvania State University, University Park, PA 16802-1401 USA (e-mail: huy25@psu.edu).

Color versions of one or more of the figures in this article are available online at https://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2020.2967030

interacting behaviors among failure modes in AMSs, leading to a big discount to the effectiveness of performance analysis.

An AMS consists of many controlled machines finishing different operations, such as machining and inspecting operations [20], [21]. Similar to the fact that there are many assembled components in reliability analysis of a finished product [22], [23], these production activities also make great contributions to the state of missions in an AMS. To evaluate the performance, various models have been established to depict activities in manufacturing systems, such as the quality-reliability-coeffect model of a multistation manufacturing process [24], Bernoulli reliability and quality model considering quality–quantity coupling [8], and mission reliability model based on operational quality data [25]. Although both machine failures and defective products were taken into account, these publications failed to consider the important influence of quality inspection on competing failures. Note that as one discrete event system, two types of competing failure coexist in the AMS with serial stations, where the quality inspection provides vital links between them. First, machines will fail under the impact of continuous degradation caused by abrasion and discrete shock caused by unqualified inputs, belonging to the first type of competing failure. Second, inspection decesions affect whether an unqualified product moves to next station, leading to the second type of competing failure. Out of question, inspection process makes the competing failure more complicated. However, the role of inspection process has always been ignored in previous studies.

In addition, manufacturing is becoming more and more oriented by services, which leads to an increasing demand for highly reliable systems [26]. To analyzing the service level of a manufacturing system, bianry mission reliability considering binary components [27] or multistate components [25], [28] has been studied, providing production organizer with more valuable information. However, how to evaluate multistate mission reliability under the influence of multiple competing failure modes is still a challenging problem.

In reliability engineering, the decision diagram method is an effective tool to evaluate multistate systems. Among relevant studies in the state of the art, multivalued decision diagram is usually applied to depict multiple possibilities of system performance [29], [30], and the multistate phased-mission (MS-PM) model was carried out to study the performance of multistate systems subject to multiple, consecutive, and nonoverlapping phases of operation [31]–[34]. It is shown that both the decision diagram method and the MS-PM model are effective tools for performance analysis of systems with multiple states. Through phased-mission models, it becomes much easier to analyze dynamic behaviors of systems by dividing a mission into different phases, which helps capture the complex interacting behaviors among failure modes in AMSs. However, it is worth mentioning that abovementioned methods fail to consider the dynamic of component status.

In order to predict system performance more accurately, this article proposes to evaluate multistate probabilities of serial AMSs under multiple competing failures. First, a serial AMS is the primary focus in this study, and some modeling assumptions are described. Second, we divide the mission into different phases so that an MS-PM model can be exploited to depict interactive behaviors among machines, product quality, and inspection processes. Then, several decision diagram models are established to analyze dynamic states of the station and system under competing failures. At last, based on these models, an algorithm is proposed to calculate probabilities of system states, which is illustrated by simulation experiments.

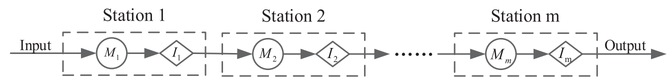


Fig. 1. Block diagram of a serial AMS with m stations.

Through analytical models and experiments, multistate probabilities of AMS's mission are obtained, and rules of system state transition are discussed under different conditions. Besides, many meaningful results are achieved, which are greatly useful for practical industrial production. In conclusion, contributions of this article can be summarized as follows.

1) A modeling framework that specifically considers and showcases the impact of inspection process on multiple competing failures is proposed.
2) Incorporating two competing failure types, an MS-PM model is constructed to depict complex interacting behaviors among components in a serial AMS, which can easily capture competing relationships among failure modes.
3) The binary decision diagram (BDD) model and multistate binary decision diagram (MBDD) model are established to characterize and model dynamic states of stations under multiple competing failures.
4) Based on the proposed MS-PM model, a novel algorithm is developed to evaluate multistate probabilities of an AMS under the dynamic states of stations.

The rest of this article is organized as follows. Section II develops an MS-PM model by analyzing the structure and properties of serial AMSs. Section III constructs decision diagram models of the station and system. Section IV proposes the evaluation algorithm of system performance based on the decision diagram models. Section V shows simulation experiments to illustrate the effectiveness of proposed methods. Finally, Section VI concludes this article.

II. Multistate Manufacturing Systems With Phased Missions

A. System Descriptions

The propagation of unqualified products will occur only between stations connected in series. Therefore, analysis of multiple competing failures will be executable only in system structures with serial stations, such as the serial, serial–parallel, and cycle systems. Here, the serial manufacturing system with imperfect inspection process will be studied. Other systems owning serial stations can be branched based on the station models proposed in this article.

The station is the basic unit of an AMS and has two key constituents: machine M and inspection process I, which are connected in series, as shown in Fig. 1. In addition, materials can be considered as inputs of the system, and end products as outputs. Obviously, outputs of each station are inputs of the next station. Considering impacts on the execution of a mission, the product is also one constituent of the manufacturing system, because it is not only the mission itself but also the carrier of propagated failure. Therefore, besides the machine and inspection process, product P (machining quality) is another key constituent in the performance evaluation of manufacturing system.

In a discrete manufacturing system, products are usually machined one by one or in batch. For the demand n in a manufacturing system with m stations, there will be m products processed respectively in stations 1–m at the same time. The time between starting and finishing processing these m products in their respective stations is a phase. In view of this property, the discrete-part manufacturing process actually can be modeled as one kind of phased-mission systems, which consist of multiple, consecutive, nonoverlapping phases of machining. Therefore, a mission with the demand of n products is divided into n phases, and mission status can be evaluated based on the performance of each phase h $(0 \leq h \leq n)$. Specifically, a mission in an AMS can be considered to own $(n+2)$ states, ranging from the perfect state to complete failure. When any machine fails, mission will be in the state of halt failure (denoted by F_{n+1}); when all machines, products, and inspections do not fail, the mission will be in the perfect state (denoted by F_0); when no machine fails but product or inspection failure occurs, the mission will be in intermediate states, which can be denoted by F_k, $(k = 1,2,\ldots,n)$, with k being the number of product losses caused by product and inspection failures. Therefore, the AMS is also one multistate system.

B. Analysis of System Properties

Before analyzing the properties, some assumptions should be taken into account as follows.

1) The phase durations are fixed and independent of the system state, and perfect time balance is considered.
2) Product transmission between stations are reliable, and the transmission time is not considered.
3) If there is no inspection process in real AMSs, all the products can be considered to pass the test, and the inspection process is virtual.
4) System inputs (same with inputs of Station 1) are always reliable, namely materials are qualified.
5) Considering the failure isolation effect of inspection, all unqualified products discovered by inspection will be discarded; in addition, considering secondary propagation of a pernicious product will be a small probability event, all pernicious products (inputs) will be identified and discarded by the inspection process of next station.
6) If no input, the station will be in starvation, whose machine will still operate without machining product.
7) The probability of machine failure (fails and halts) will increase randomly in one phase if propagated unqualified products occur in previous station in the last phase.
8) Machine states, inspection process, and product quality in the same station are independent in the same phase.

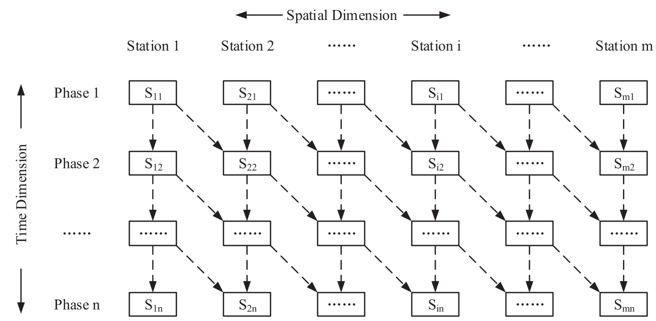


Fig. 2. States interactive relations under propagated failure in serial AMSs.

As one MS-PM system, the mission of a serial AMS can be spread in spatial and time dimensions, as shown in Fig. 2. Square nodes represent states of stations in each phase, and dotted arrows represent relations of states. According to the assumptions and state relations, three properties can be concluded about the AMS.

1) Property 1: Time-Delayed Propagation of Failure: In each station, the propagation of unqualified products is not instantaneous. It will take into effect in next station in the next phase, which represents the time delay of one phase, as the dotted arrows pointing lower right shown in Fig. 2. This property makes it possible to study formations and effects of failures separately, which reduces the research difficulty caused by studying both of them. This provides the prerequisite to model the decision diagram of a system.

2) Property 2: Accumulative Degradation Failure: In each station, effect of unqualified products on machine failure shows cumulation property. Namely, machine degradation will be accumulated from phase to phase, as the dotted arrows pointing down shown in Fig. 2. This property is due to machine degradation that is a no-decreasing process. This is one of the main factors causing interactive behaviors in a manufacturing system.

3) Property 3: Dynamic States: In this model, the state number of a station is not stationary but dynamic. When the input is not available (in starvation), the station will only have two states: The machine operates without processing products or fails and halts. But when the qualified input is available, the station will have four states because the product quality is considered. This is resulted from interactive behaviors in a manufacturing system, which is also the emphasis and difficulty for performance analysis of AMSs when considering multiple competing failures. More details will be provided in Section III-A.

III. Modeling of Multistate Manufacturing Systems With Phased Missions and Imperfect Inspection Processes

A. Decision Diagram Modeling for the Station With Dynamic States

In manufacturing systems, station performance is concerned as the probability that it is in one state at the end of one phase. According to descriptions presented in Section II, machine M, inspection process I, and product P will affect the performance of

TABLE I
EVENT SET OF COMPONENTS IN A STATION

Event	Consequence
E_{MS0} / E_{MS1}	Machine operates successfully / fails and halts
E_{QS0} / E_{QS1}	Quality successes / fails
E_{PS0} / E_{PS1}	Product dimensions satisfy / do not satisfy the qualifications
E_{IS0} / E_{IS1}	Inspection process gives right / wrong decision

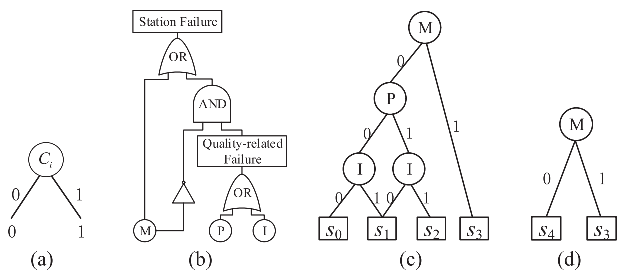


Fig. 3. BDD models and fault tree model in a station. (a) BDD for component state. (b) Fault tree of station; (c) MBDD for station states when no starvation. (d) BDD for station states when in starvation.

a station, each of which can be considered as a binary component that owns mission success state (0) and failure state (1). Here, failures of the three components are defined as follows.

1) Machine failure: Machine breakdown occurs in the machining process (State 1).
2) Product failure: Machined dimensions of a product do not satisfy the qualifications (State 1).
3) Inspection failure: The inspection process gives a wrong decision about the product quality state (state 1).

In addition, quality success (State 00) is the intersection of both mission successes of product *P* (State 0) and inspection *I* (State 0). Therefore, the defination of quality-related failure is:

4) Quality-related failure: Any failure of product *P* and inspection *I* occurs (State 11, 01, or 10).

Based on these depictions, event set of components is illustrated in Table I.

Assume that a machine has a failure rate *r*(*t*) and processing time Δt for each product, the probability that machine fails and halts during the operation can be obtained as follows:

$$\Pr(E_{MS1}) = r\,(t) \cdot \Delta t. \tag{1}$$

According to the BDD method, states of each component can be illustrated by a Boolean variable C_i (*i* refers to *M*, *P*, or *I*), which corresponds to a basic event that can be represented through the *if–then–else* (*ite*) format as *ite*(c_i, 1, 0), where c_i is the probability that the component *i* is in State 1. Therefore, as one binary component, machine *M*, product *P,* and inspect process *I* have the similar binary decision diagram to depict their basic events *ite*(c_i, 1, 0), each encoding the event of one component C_i (*M*, *P*, or *I*) being in the state of *k* ($k = 0, 1$), as shown in Fig. 3(a). Here, two outgoing edges represent two states of a component.

If inputs are qualified (no starvation), mission failure of a station could be caused by two events, i.e., the machine failure and quality-related failure. If the machine fails and halts, the station is already in failure state before it finishes processing the product. Therefore, quality state will not play a part in mission states of a station. On the contrary, if quality-related failure takes effect in station states, the machine must operate successfully so that it finishes processing the product. According to the function and reliability definition, a station's fault tree can be established, as shown in Fig. 3(b). The mission failure probability of a station can be calculated as

$$\begin{aligned}\Pr\,(E_{SS1}) &= \Pr(E_{SS1}|E_{MS1}) \cdot \Pr(E_{MS1}) \\ &\quad + \Pr(E_{SS1}|E_{MS0}) \cdot \Pr(E_{MS0}) \\ &= \Pr(E_{MS1}) + \Pr(E_{QS1}) \cdot \Pr(E_{MS0})\end{aligned} \tag{2}$$

where $\Pr(E_{SS1}|E_{MS1})=1$, and $\Pr(E_{SS1}|E_{MS0})=\Pr(E_{QS1})$. In addition, a quality-related failure event consists of two statistically independent subevents, inspection failure and product failure. So, the probability of quality-related failure can be obtained as

$$\begin{aligned}\Pr\,(E_{QS1}) &= \Pr(E_{PS1}) \cdot \Pr(E_{IS1}) + \Pr(E_{PS1}) \\ &\quad \cdot \Pr(E_{IS0}) + \Pr(E_{PS0}) \cdot \Pr(E_{IS1}) \\ &= \Pr(E_{PS1}) + \Pr(E_{PS0}) \cdot \Pr(E_{IS1}).\end{aligned} \tag{3}$$

Therefore, the mission failure probability of a station can be rewritten as

$$\begin{aligned}\Pr\,(E_{SS1}) &= \Pr(E_{MS1}) + \Pr(E_{MS0}) \cdot \Pr(E_{PS1}) \\ &\quad + \Pr(E_{MS0}) \cdot \Pr(E_{PS0}) \cdot \Pr(E_{IS1}).\end{aligned} \tag{4}$$

In addition, the event $E_{PS1} \cap E_{IS1}$ represents that the propagation of quality-related failure occurs; the event $(E_{PS1} \cap E_{IS0}) \cup (E_{PS0} \cap E_{IS1})$ represents that local quality-related failure occurs. Their probabilities can be obtained by the following equations:

$$\begin{aligned}\Pr\,(E_{PF}) &= \Pr\,(E_{PF}|E_{MS1}) \cdot \Pr\,(E_{MS1}) \\ &\quad + \Pr\,(E_{PF}|E_{MS0}) \cdot \Pr\,(E_{MS0}) \\ &= 0 \cdot \Pr\,(E_{MS1}) + \Pr\,(E_{PS1}) \\ &\quad \cdot \Pr\,(E_{IS1}) \cdot \Pr\,(E_{MS0}) \\ &= \Pr\,(E_{PS1}) \cdot \Pr\,(E_{IS1}) \cdot \Pr\,(E_{MS0})\,.\end{aligned} \tag{5}$$

$$\begin{aligned}\Pr\,(E_{LF}) &= \Pr\,(E_{LF}|E_{MS1}) \cdot \Pr\,(E_{MS1}) \\ &\quad + \Pr\,(E_{LF}|E_{MS0}) \cdot \Pr\,(E_{MS0}) \\ &= 0 \cdot \Pr\,(E_{MS1}) + (\Pr\,(E_{PS1}) \cdot \Pr\,(E_{IS0}) \\ &\quad + \Pr\,(E_{PS0}) \cdot \Pr\,(E_{IS1})) \cdot \Pr\,(E_{MS0}) \\ &= \Pr\,(E_{PS1}) \cdot \Pr\,(E_{IS0}) \cdot \Pr\,(E_{MS0}) \\ &\quad + \Pr\,(E_{PS0}) \cdot \Pr\,(E_{IS1}) \cdot \Pr\,(E_{MS0})\,.\end{aligned} \tag{6}$$

Therefore, $\Pr(E_{SS1}) = \Pr(E_{MS1}) + \Pr(E_{PF}) + \Pr(E_{LF})$. Referring to the fault tree, an MBDD model for station states is established by the ordering $M > P > I$, as illustrated in Fig. 3(c). The four sink nodes, respectively, represent the station being in the states of mission success (s_0), local quality-related failure (s_1), propagated quality-related failure (s_2), and machine failure

(s_3). Therefore, in the condition of qualified inputs, station is a quaternion subsystem with four states.

If inputs are unqualified (no starvation), a station will only have two states: the local quality-related failure and machine failure, which is a binary subsystem with the same *if–then–else* format in Fig. 3(a). In this condition, $\Pr(E_{PS1}) = 1$, and $\Pr(E_{IS1}) = 0$ according to Assumption (5). So $\Pr(E_{LF}) = \Pr(E_{MS0})$.

If there is no input (starvation), the performance of a station is only affected by machine states. Therefore, the station is one binary subsystem, which can be illustrated by a bianry decision diagram, as shown in Fig. 3(d). Here, a station has two states: the state (s_3) of machine failure and the state (s_4) of machine's operation without machining product. The mission failure probability of a station is $\Pr(E_{SS1}) = \Pr(E_{MS1})$.

B. MS-PM System With Time-Delayed Propagation of Failure

As analyzed in Section III-A, quality-related failure has two modes: the propagated failure and local failure. And propagated failure will affect the performance of next machines. A serial AMS can be depicted as *S*(*n*, *m*), which has *m* stations with the product demand *n*. The total demand can be separated into *n* phased missions, and machine states in each station *i* (*i* = 1, 2, …, *m*) may be discrepant for different task phases *j* (*j* = 1, 2, …, *n*). According to the total probability formula, the probability of machine's failure is

$$\begin{aligned}\Pr\left(E_{MS1ij}\right) =& \Pr\left(E_{MS1ij}|E_{PF(i-1)(j-1)}\right)\\ &\cdot \Pr\left(E_{PF(i-1)(j-1)}\right)\\ &+ \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right)\\ &\cdot \Pr\left(E_{\overline{PF(i-1)(j-1)}}\right). \end{aligned} \tag{7}$$

According to Assumption (7), we have

$$\Pr\left(E_{MS1ij}|E_{PF(i-1)(j-1)}\right) \geq \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right).$$

So there must be a probability increment Δp that fits (8). Assume that the probability increment Δp is a stochastic variable that follows beta distribution *B*(*a, b*), which can depict the stochastic phenomenon that stochastic variables locate in the interval [0, 1] by assigning different values to *a* and *b* [35]

$$\begin{aligned}&\Pr\left(E_{MS1ij}|E_{PF(i-1)(j-1)}\right) - \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right)\\ &= \Delta p. \end{aligned} \tag{8}$$

Finally, (7) can be rewritten as (9). According to (9), it is obvious that the effect of propagated quality-related failure has properties of time delay and accumulations

$$\begin{aligned}\Pr\left(E_{MS1ij}\right) =& \Pr\left(E_{MS1ij}|E_{PF(i-1)(j-1)}\right)\\ &\cdot \Pr\left(E_{PF(i-1)(j-1)}\right)\\ &+ \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right)\\ &\cdot \Pr\left(E_{\overline{PF(i-1)(j-1)}}\right)\\ =& \left(\Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right) + \Delta p\right)\\ &\cdot \Pr\left(E_{PF(i-1)(j-1)}\right)\\ &+ \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right)\\ &\cdot \Pr\left(E_{\overline{PF(i-1)(j-1)}}\right)\\ =& \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right)\\ &\cdot\left(\Pr\left(E_{PF(i-1)(j-1)}\right) + \Pr\left(E_{\overline{PF(i-1)(j-1)}}\right)\right)\\ &+ \Delta p \cdot \Pr\left(E_{PF(i-1)(j-1)}\right)\\ =& \Pr\left(E_{MS1ij}|E_{\overline{PF(i-1)(j-1)}}\right) + \Delta p\\ &\cdot \Pr\left(E_{PF(i-1)(j-1)}\right). \end{aligned} \tag{9}$$

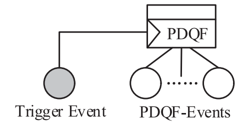


Fig. 4. General structure of a PDQF gate.

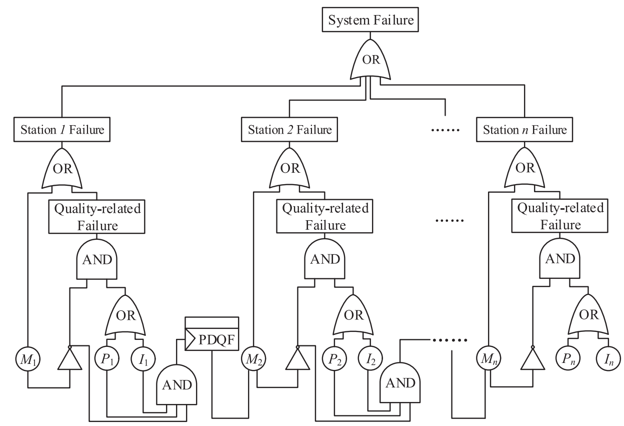


Fig. 5. Dynamic fault tree of serial AMSs.

Considering these characteristics, a new gate of propagation delay of quality-related failure (PDQF) is proposed to depict the time-delayed accumulative behavior in manufacturing systems, as shown in Fig. 4. When a trigger event (propagated quality-related failure) occurs, there will be a probability increment Δp being accumulated for the failure of dependent machines in the next phase.

According to the fault tree of stations in Section III-A, as one serial system, the dynamic fault tree of AMSs can be established using PDQF gate and OR gate for a single phase. As shown in Fig. 5, the trigger event of the PDQF gate is the propagated quality-related failure, which can be represented by $E_{MS0} \cap E_{PS1} \cap E_{IS1}$.

C. Multistate Multivalue Decision Diagram Modeling for the MS-PM Systems

For system $S(n, m)$ with m stations and n product demands, assume that initial states of all stations are mission success state (s_0) in phase $h = 0$. According to Section II-A $(n + 2)$ mission states exist in the MS-PM model: the perfect state (F_0), halt state (F_{n+1}), and n intermediate states F_k that k quality-related failures occur ($k = 1, 2, \ldots, n$). In a decision diagram, each mission state of a system can be represented by one sink node. Therefore, the multistate multivalue decision diagram (MMDD) can be used to represent this MS-PM system, which consists of several nonsink nodes and $(n + 2)$ sink nodes. The phase state X_h is defined as a combination of station states in the phase h, which can be illustrated by a $1 \times m$ dimensional matrix, namely $X_h = [S_{1h}\ S_{2h}\ \ldots\ S_{mh}]$, where S_{ih} is the state of station i in phase h. For the convenience of display, we use the numbers 0–4 to represent the station states s_0, s_1, s_2, s_3, and s_4 in a matrix. So, in the initial phase $h = 0$, $X_0 = [0\ 0\ \ldots\ 0]$. Additionally, initial phase state is also the initial state for a mission, namely $G_0 = X_0 = [0\ 0\ \ldots\ 0]$, and G_0 is also the root node in an MMDD. In any phase h $(1 \le h \le n)$, nonsink nodes G_h can be represented by an $(h + 1) \times m$ dimensional matrix, as shown in the following equation:

$$G_h = \begin{bmatrix} G_{h-1} \\ X_h \end{bmatrix} = \begin{bmatrix} S_{10} & S_{20} & \cdots & S_{m0} \\ S_{11} & S_{21} & \cdots & S_{m1} \\ \cdots & \cdots & \cdots & \cdots \\ S_{1h} & S_{2h} & \cdots & S_{mh} \end{bmatrix}. \quad (10)$$

Affected by the time-delayed propagation of quality-related failure, stations represent dynamic behaviors. A station will have inputs and become a quaternion station in next phase when its previous station is in mission success state (s_0); a station will have no qualified inputs and become a binary station in next phase when its previous station is in quality-related failure states (s_1 or s_2) or the state of operation without machining products (s_4). Obviously, dynamic behaviors of stations will cause the change of system phase state X_h. In summary, three kinds of phase states will occur: states with only binary stations, states with only quaternion stations, and states with both binary and quaternion stations. For phase states with only binary stations, all stations are in starvation or have unqualified inputs; for phase states with only quaternion stations, all stations have qualified inputs. Each kind of phase states will have different outgoing edges, which will be analyzed below.

If phase states X_{h-1} have only quaternion stations in phase $h - 1 (2 \le h \le n)$, the nonsink node G_{h-1} has 4^m outgoing edges based on Shannon's decomposition rule [36], which represent different phase states of a system. In these outgoing edges, 3^m outgoing edges will be connected to nonsink nodes G_h in phase h, which represent that the system will still operate in perfect state or intermediate states at the end of phase h; $4^m - 3^m$ outgoing edges that at least one machine fails will be connected to the sink node "halt failure," which represents that the system will be in the state of halt failure at the end of phase h, as shown in Fig. 6.

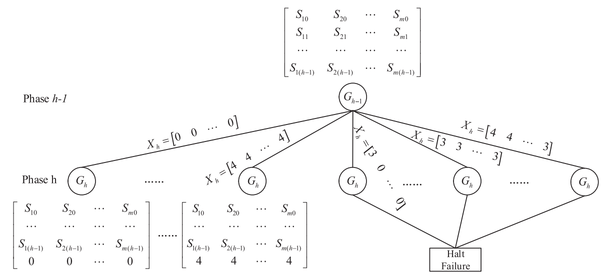


Fig. 6. Connection pattern of an MMDD node G_{h-1} in phase states with only quaternion stations.

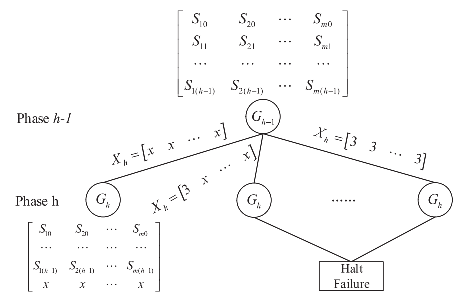


Fig. 7. Connection pattern of an MMDD node G_{h-1} in phase states with only binary stations.

If phase states X_{h-1} only have binary stations in phase $h - 1 (2 \le h \le n)$, the nonsink node G_{h-1} has 2^m outgoing edges. In these outgoing edges, only one will be connected to nonsink nodes G_h in phase h, which represents that the system will still operate without machine's halt failure at the end of phase h; $2^m - 1$ outgoing edges that at least one machine fails will be connected to the sink node "halt failure," as shown in Fig. 7. The station state S can be state s_1 or s_4, which will be illustrated in Section IV-A.

In phase $h - 1 (2 \le h \le n)$ with phase states X_{h-1} that have both binary and quaternion stations, assume that f stations are in the state of local quality-related failure (s_1) and g stations are in the state of propagated quality-related failure (s_2). Nonsink node G_{h-1} has $4^{m-f-g} \times 2^{f+g}$ outgoing edges, in which $(4^{m-f-g} - 3^{m-f-g}) \times (2^{f+g} - 1)$ outgoing edges that have at least one machine fails will be connected to the sink node "halt failure," and $(4^{m-f-g} \times 2^{f+g} - (4^{m-f-g} - 3^{m-f-g}) \times (2^{f+g} - 1))$ outgoing edges will be connected to nonsink nodes G_h in phase h, which represent that the system will still operate in intermediate states at the end of phase h.

IV. Performance Analysis of Multistate Manufacturing Systems With Phased Missions

A. MMDD Model Formulation

In this section, a new algorithm is proposed for the performance evaluation of manufacturing systems based on the MMDD model. As we know, multistate systems have a large number of variables to represent their states, resulting in the computation explosion and poor efficiency, especially for large-scale systems [37]. Depending on the analysis presented in Section III-C, the proposed MS-PM system is a large-scale multistate system, and its nonsink nodes will increase exponentially

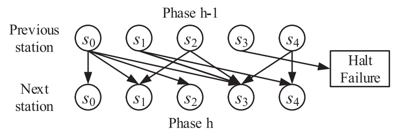


Fig. 8. State transition relations between stations.

in each phase. Therefore, some simplification principles should be provided to reduce the computational complexity.

Each nonsink node will produce more nonsink nodes and some sink nodes in next phase during computation. Therefore, the phase-by-phase explosive growth of nonsink nodes is the main factor contributing to the low computational efficiency. Out of question, it will be more effective for the computation when reducing the number of nodes in an earlier phase. Here, a method for efficiently recognizing the equivalent phase states are proposed, which is useful for merging identical outgoing edges when they are produced in each phase.

Definition: Set $\{X_h, N_h\}$. Given a nonsink node G_h, X_h is the phase state in phase h, and N_h is the number of local quality-related failure (s_1) in the node state matrix G_h.

All identical outgoing edges in one phase can be efficiently recognized and merged when they have the same set $\{X_h, N_h\}$. In addition, two merging principles can be concluded according to dynamic station states. State transition relations between neighboring stations are illustrated in Fig. 8. If the previous station is in state s_0 in phase $h-1$, the next station will be in one of four states ($s_0/s_1/s_2/s_3$) in phase h, which is a quaternion station; if the previous station is in states $s_1, s_4,$ or s_2 in phase $h-1$, the next station will be only in one of two states (s_3/s_4 or s_1/s_3) in phase h, which is a binary station. Obviously, states s_1 and s_4 have the same states of next station, and phase states containing state s_3 will be connected with the sink node "Halt Failure." According to these two phenomena, two merging principles can be obtained.

Principle 1: When outgoing edges have phase states X_h containing state s_3, the nodes will be merged into the sink node "Halt Failure."

Principle 2: The state s_1 can be changed into state s_4 in each phase state X_h; simultaneously, the number of exchanges will be added in N_h; then, all nonsink nodes with the same set $\{X_h, N_h\}$ can be merged.

B. MMDD Generation and System Evaluation

On the basis of definitions and principles presented in Section IV-A, an algorithm flowchart of both MMDD generation and system performance evaluation underlying the proposed MS-PM model is presented in Fig. 9, which contains three steps.

Step 1: Parameters of both basic events $\{E_{MS1}, E_{PS1}, E_{IS1}\}$ and probability increment Δp for each station are known. At the beginning of each phase, all phase state sets $\{X_{h-1}, N_{h-1}\}$ of phase $h-1$ are known. Then, the following four operations should be finished.

Operation 1: Calculate state probability matrices of stations under the parent nonsink node. States of each station are determined by the state of its previous station, as shown in Fig. 8. If the previous station of one station is in state s_2, the probability of

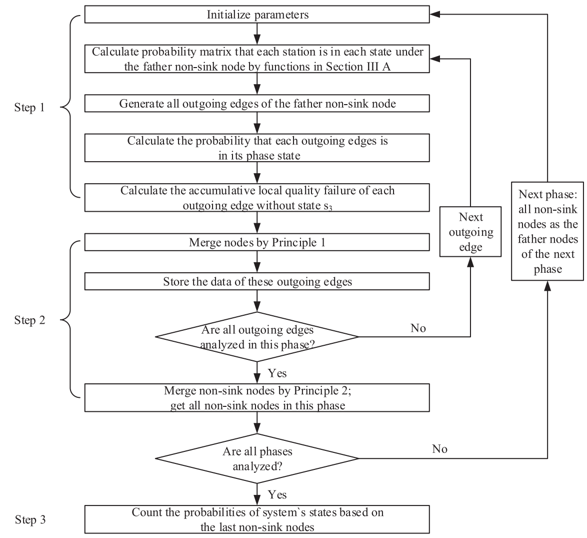


Fig. 9. Algorithm flowchart of system MMDD generation and performance evaluation.

machine failure will be calculated by (1) and (9); for other conditions, the probability of machine failure will be obtained only by (1). Then, probabilities of states in phase h can be calculated for all stations by equations presented in Section III-A.

Operation 2: Generate all outgoing edges of parent nonsink nodes, where each parent nonsink node is one phase state set $\{X_{h-1}, N_{h-1}\}$ of phase $h-1$.

Operation 3: Compute the probability that each new outgoing edge is in its phase state X_h.

Operation 4: Calculate the number N_h of accumulative local quality-related failure (s_1) for each new outgoing edge without state s_3.

Step 2: Simplify the MMDD model. The following two operations should be accomplished in this step.

Operation 1: According to Principle 1, merge sets $\{X_h, N_h\}$ containing state s_3 and add their state probabilities to the halt failure node; this operation can be finished before or after all outgoing edges are analyzed.

Operation 2: Depending on Principle 2, merge nonsink sets $\{X_h, N_h\}$ and obtain all nonsink nodes in phase h; this operation should be finished after all outgoing edges are analyzed.

Step 3: After all phases are analyzed, count the probabilities of system states based on all nonsink sets $\{X_n, N_n\}$ in phase n, and get one halt failure node and $(n+1)$ sink nodes with quality-related failure numbers from 0 to n.

V. Simulation Experiments

Providing good approximations to machine failure [26], [38] or fitting many different failure patterns [39], [40] makes the exponential and Weibull distributions to become two popular distributions used in the analysis of manufacturing systems. Here, two examples are provided to illustrate the effectiveness of proposed performance evaluation method for serial AMSs, where machine life follows exponential distribution and Weibull distribution, respectively. Assume that machines with exponential and Weibull life distribution have the same mean life, namely $EX(Y_E) = EX(Y_W)$, whose failure rates are presented

TABLE II
STATION PARAMETERS FOR SIMULATION EXPERIMENTS

No	Distributions of Life ($*10^{-5}$) Exp. λ	Weib. α	β	Distributions of Δp Beta a	b	Failure Rates ($*10^{-2}$) Pro. E_{PS1}	Ins. E_{IS1}
1	1.20	1.190	1.02	$0.73*10^{-3}$	7.33	1.03	0.86
2	0.60	0.583	1.08	$1.57*10^{-3}$	15.67	0.68	0.64
3	8.00	0.785	1.05	$1.15*10^{-3}$	11.50	0.98	0.72
4	4.00	0.391	1.06	$2.40*10^{-3}$	24.00	0.75	0.98

in functions (11) and (12), respectively. In addition, the shape parameter of the Weibull distribution satisfies $\beta > 1$ in this article, which indicates that machines have increasing failure rates over time due to degradation. Exponential machines have constant failure rates, which represents that they have steady continuous degradation during the mission

$$r_E(t) = \lambda \tag{11}$$

$$r_W(t) = \alpha\beta(\alpha t)^{\beta-1}. \tag{12}$$

Probability increments $\Delta \boldsymbol{p}$ caused by unqualified inputs are random variables following beta distributions with the same expectation but different variances, namely the same $\mathrm{EXP}(Y) = a/(a+b)$ for each station. In beta distributions, the variances $V(Y) = (a+b)/((a+b)^2 + (a+b+1))$ are considered to have inversely proportional relationship with machines' mean life. So, under these conditions of expectations and variances, machines with less mean life will be more erratic when influenced by unqualified inputs. As one system with perfect time balance, processing time is considered to be 6.67 min per product in each machine. Under the conditions mentioned above, parameters of stations are obtained by random generation, as shown in Table II.

In the simulation, different station numbers (2, 3, and 4) and different mission scales (10–300) are analyzed. The probabilities of the perfect state, intermediate states, and complete failure state are obtained for the simulated manufacturing systems.

A. Perfect State of the System

For the perfect state without quality-related failure and machine failure, systems with 2, 3, and 4 stations are studied, as shown in Fig. 10.

Obviously, probabilities of the perfect state will decrease when mission scales increase in any system, and they will be close to zero when mission scales are large enough. This represents that the number of system states will explode when mission scales become large, and probabilities of the perfect state will be attenuated. In addition, the more the stations are, the lesser perfect-state probability a system will have. It is because there will be more failure locations when station numbers increase, which will lead to a rise of failure probability. On the other hand, even though it is not greatly obvious, it can also reflect the difference between perfect-state probabilities for different life distributions. When missions are less, systems with Weibull machines have higher perfect-state probabilities than those with exponential machines, and this advantage will disappear when scales of missions become larger. This can be concluded as two reasons: first, owing the same mean life, the system with Weibull machines has a lower failure rate than the exponential one in early stages of system operation (where t is less); second, the probability of perfect state is attenuated by the increment of system state numbers when scales of missions become larger.

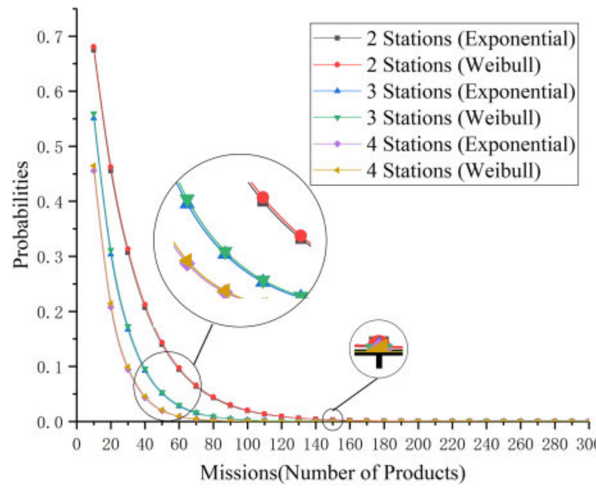


Fig. 10. Probability curves of system perfect states.

B. Intermediate States of the System

For the intermediate states that have quality-related failure but no machine failure, different mission scales (10–130) are studied, as shown in Fig. 11. Obviously, whether exponential or Weibull life distribution, probability distribution curves of intermediate states are diverse for different mission scales. We define the highest point of each curve in Fig. 11(a) and (b) as the the maximum probability event, which shows the most likely number of quality-related failure during the mission. It is obvious that maximum probability events will have more quality-related failure when mission scales become larger, but lower probability. This also represents the explosion of state quantity and attenuation of state probabilities when mission scales become larger. In addition, due to the isolation effect of inspection processes, the probability is so low that massive quality-related failure rarely occurs in one mission. Therefore, number of quality-related failure is limited in (0, 20) in these examples, and occurrences of more quality-related failure can be regarded as small probability events that have probabilities close to zero.

On the other hand, numbers of quality-related failure will be much more centralized for systems with less stations, as shown in Fig. 11(c). Similarly, the maximum probability event also has more quality-related failure with lower probability when stations become more. In addition, Fig. 11 also shows that no matter how large the mission scale is, the AMSs with Weibull distributions will have a higher probability of quality-related failure than the ones with exponential distributions. This represents that quality-related failure of systems with increasing degradation appears much more frequently than systems with stable degradation.

To analyze the difference of exponential and Weibull life distributions, systems with 2, 3, and 4 stations are studied. Assume that probabilities of intermediate states are $P = \{p(j), j = 1,2,\ldots,n\}$, which means the probability that a system has j quality-related failure is $p(j)$. We define the expectation of

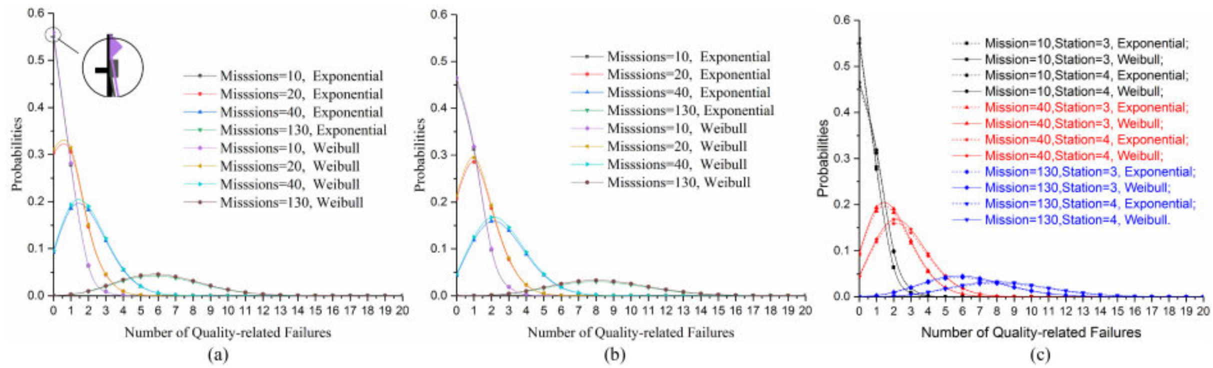


Fig. 11. Probability curves of quality-related failures in serial AMS. (a) Stations = 3. (b) Stations = 4. (c) Mission = 10/40/130.

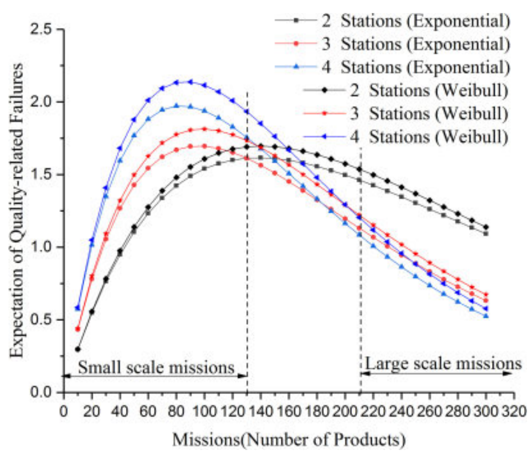


Fig. 12. Expectation curves of quality-related failure.

quality-related failure as follows:

$$\mathrm{EXP}(P) = \sum_{j=1}^{n} j \times p(j). \tag{13}$$

Then, expectation curves of quality-related failure for different systems are obtained, as shown in Fig. 12.

In all conditions, expectation curves increase first and then decrease when mission scales increase, which have crest values. In addition, expectations will present two different characteristics for large and small mission scales in the same life distribution. Systems with more stations will have much larger expectations of quality-related failure in small scale missions, but systems with less stations have much larger expectations in large scale missions. The former is consistent with our common sense, but why the latter happens?

Two reasons can be concluded for this phenomenon. First, the probability that a system fails and halts will be much higher during the operation of large scale missions. In other words, halt failure is the state most likely to occur during the operation, as shown in Fig. 13. Therefore, the sum of all intermediate states' probabilities in large scale mission is much lower than small-scale one. Second, the number of quality-related failure in large scale mission is more dispersed than a small one. Although expectations are much less, the system will be much easier to subject to halt failure in large scale missions. In addition,

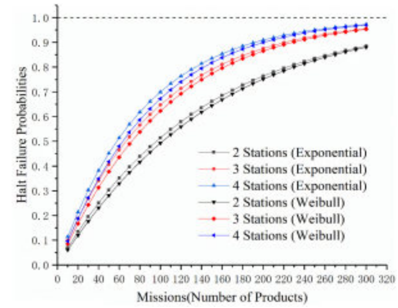


Fig. 13. System halt failure probability curves.

systems with Weibull machines have much larger expectations than those with exponential. This further verifies the law that quality-related failure of systems with increasing degradation appears much more frequently than systems with stable degradation.

C. Halt Failure in the System

For the halt failure that has at least one machine failing and halting, the probability will increase and close to one when mission scale becomes larger, as shown in Fig. 13. Obviously, systems with more stations will fail and halt much more frequently due to the increase in failure locations. In addition, a system with Weibull machines has less probability of halt failure than the one with exponential in these examples, but this trend becomes inconspicuous when mission scales become larger. The reason is that failure rates of Weibull distribution are less than exponential distribution in small mission scales (where t is small); but it is inverse for large mission scales. So, the failure probability curve of Weibull distribution will gradually catch up with and exceed the one of exponential distribution.

D. Discussion of Experimental Results

Simulation experiments provided the multistate probabilities of a mission in serial AMSs and showed some strong laws about mission states with station numbers, mission scales, and machine life distributions. According to experiments, probabilities of the perfect and intermediate states would be attenuated with the increase in mission scale or station quantity. In intermediate states, the isolation effect of inspection processes was also proved. Through this effect, the number of quality-related failure was limited in some scopes (such as [0, 20] in the experiments) and larger quantity of quality-related failure would happen in the small probability close to zero. These observations are very meaningful and useful for industrial production.

In industrial applications, quality and delivery date are two important indicators in manufacturing. Before starting a mission or order, its execution can be assessed in advance, and the delivery period and quality status can be judged by our proposed models. For example, the maximum probability event will help the system to learn the most likely loss of the mission, or expectation curves of quality-related failure can remind us to avoid mission scales with high expectation of quality-related failure. Therefore, the proposed models can make industrial production more transparent, which is an important aspect of industrial informationizion. This will provide manufacturing systems with more time to respond to possible situations. Additionally, in the era of industrial 4.0, the application of sensors will be more common, which will make it easier to obtain the operation data or reliability status of machines or other components. Combined with the proposed performance evaluation model, it will make the intelligent decision of manufacturing system possible.

At the technical level, previous models usually evaluated binary states of a mission, which only provided the probability that a mission could be finished in a limit time [25], [27]. According to simulation experiments presented in this article, richer information about mission status is revealed. Additionally, experiments also illustrate the universality of our models, which can be applied in multiple machine life distributions. This is another strength compared with previous models, such as the one only considering machines with gamma and Wiener degradation [27].

VI. Conclusion and Future Work

In this article, we made new contributions by proposing a competing failure model to analyze system performance by evaluating mission states in a serial AMS. The proposed model provides more detailed information about mission states than the conventional binary model, which can also be generally applicable to any arbitrary types of machine life distributions. One potential limitation is that the failure rate, which is that products do not satisfy the qualification, is assumed to be a constant. In the real-world settings, this rate may change with machine degradation in some systems. In the future research, this model can be further exploited by considering variable failure rates, as well as the relation between product failure and machine degradation. Finally, this model does not solve the hard problem of computational efficiency radically, although some simplifications have been implemented. As mission scale and station quantity increase, the number of system states will also explode, leading to the decrease in computational efficiency. Therefore, it will be also necessary to investigate parallel implementations for more efficient algorithms in the future.

References

[1] H. Hu and Y. Liu, “Supervisor synthesis and performance improvement for automated manufacturing systems by using petri nets,” *IEEE Trans. Ind. Informat.*, vol. 11, no. 2, pp. 450–458, Apr. 2015.

[2] U. D. Atmojo, Z. Salcic, and K. I. Wang, “Dynamic reconfiguration and adaptation of manufacturing systems using SOSJ framework,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 6, pp. 2353–2363, Jun. 2018.

[3] R. Harrison, D. Vera, and B. Ahmad, “Engineering methods and tools for cyber–physical automation systems,” *Proc. IEEE*, vol. 104, no. 5, pp. 973–985, May 2016.

[4] S. Iarovyi, W. M. Mohammed, A. Lobov, B. R. Ferrer, and J. L. M. Lastra, “Cyber–physical systems for open-knowledge-driven manufacturing execution systems,” *Proc. IEEE*, vol. 104, no. 5, pp. 1142–1154, May 2016.

[5] J. Otto, B. Vogel-Heuser, and O. Niggemann, “Automatic parameter estimation for reusable software components of modular and reconfigurable cyber-physical production systems in the domain of discrete manufacturing,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 275–282, Jan. 2018.

[6] R. C. Luo and C. Kuo, “Intelligent seven-DoF robot with dynamic obstacle avoidance and 3-D object recognition for industrial cyber–physical systems in manufacturing automation,” *Proc. IEEE*, vol. 104, no. 5, pp. 1102–1113, May 2016.

[7] A. Bonci, M. Pirani, and S. Longhi, “Tiny cyber-physical systems for performance improvement in the factory of the future,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 3, pp. 1598–1608, Mar. 2019.

[8] S. M. Meerkov and L. Zhang, “Bernoulli production lines with quality-quantity coupling machines: Monotonicity properties and bottlenecks,” *Ann. Oper. Res.*, vol. 182, no. 1, pp. 119–131, Feb. 2009.

[9] A. Khaleghei and V. Makis, “Reliability estimation of a system subject to condition monitoring with two dependent failure modes,” *IIE Trans.*, vol. 48, no. 11, pp. 1058–1071, Aug. 2016.

[10] S. Hao and J. Yang, “Reliability analysis for dependent competing failure processes with changing degradation rate and hard failure threshold levels,” *Comput. Ind. Eng.*, vol. 118, pp. 340–351, Apr. 2018.

[11] K. Rafiee, Q. Feng, and D. W. Coit, “Reliability assessment of competing risks with generalized mixed shock models,” *Rel. Eng. Syst. Saf.*, vol. 159, pp. 1–11, Mar. 2017.

[12] Z. An and D. Sun, “Reliability modeling for systems subject to multiple dependent competing failure processes with shock loads above a certain level,” *Rel. Eng. Syst. Saf.*, vol. 157, pp. 129–138, Jan. 2017.

[13] L. Jiang, Q. Feng, and D. W. Coit, “Modeling zoned shock effects on stochastic degradation in dependent failure processes,” *IIE Trans.*, vol. 47, no. 5, pp. 460–470, Jan. 2015.

[14] K. Rafiee, Q. Feng, and D. W. Coit, “Reliability modeling for dependent competing failure processes with changing degradation rate,” *IIE Trans.*, vol. 46, no. 5, pp. 483–496, Jun. 2014.

[15] C. Wang *et al.*, “Competing failure analysis in phased-mission systems with multiple functional dependence groups,” *Rel. Eng. Syst. Saf.*, vol. 164, pp. 24–33, Aug. 2017.

[16] Y. Mo, L. Xing, F. Zhong, and Z. Zhang, “Reliability evaluation of network systems with dependent propagated failures using decision diagrams,” *IEEE Trans. Dependable Secure Comput.*, vol. 13, no. 6, pp. 672–683, Nov./Dec. 2016.

[17] Y. Wang, L. Xing, H. Wang, and D. W. Coit, “System reliability modeling considering correlated probabilistic competing failures,” *IEEE Trans. Rel.*, vol. 67, no. 2, pp. 416–431, Jun. 2018.

[18] Y. Lin, Y. Li, and E. Zio, “Fuzzy reliability assessment of systems with multiple-dependent competing degradation processes,” *IEEE Trans. Fuzzy Syst.*, vol. 23, no. 5, pp. 1428–1438, Oct. 2015.

[19] H. Li, D. Pan, and C. L. P. Chen, “Reliability modeling and life estimation using an expectation maximization based wiener degradation model for momentum wheels,” *IEEE Trans. Cybern.*, vol. 45, no. 5, pp. 969–977, May 2015.

[20] F. Zhou *et al.*, “Supplier portfolio of key outsourcing parts selection using a two-stage decision making framework for Chinese domestic auto-maker,” *Comput. Ind. Eng.*, vol. 128, pp. 559–575, Feb. 2019.

[21] F. Tricas *et al.*, “A petri net structure-based deadlock prevention solution for sequential resource allocation systems,” in *Proc. IEEE Int. Conf. Robot. Automat.*, 2005, pp. 271–277.

[22] S. Si, M. Liu, Z. Jiang, T. Jin, and Z. Cai, “System reliability allocation and optimization based on generalized birnbaum importance measure,” *IEEE Trans. Rel.*, vol. 68, no. 3, pp. 831–843, Sep. 2019.

[23] J. Zhao, S. Si, and Z. Cai, “A multi-objective reliability optimization for reconfigurable systems considering components degradation,” *Rel. Eng. Syst. Saf.*, vol. 183, pp. 104–115, Mar. 2019.

[24] Y. Chen and J. H. Jin, “Quality-reliability chain modeling for system-reliability analysis of complex manufacturing processes,” *IEEE Trans. Rel.*, vol. 54, no. 3, pp. 475–488, Sep. 2005.

[25] Z. Chen, Y. He, Y. Zhao *et al.*, “Mission reliability evaluation based on operational quality data for multistate manufacturing systems,” *Int. J. Prod. Res.*, vol. 57, no. 6, pp. 1840–1856, Aug. 2019.

[26] L. Wang, Y. Bai, N. Huang, and Q. Wang, "Fractal-based reliability measure for heterogeneous manufacturing networks," *IEEE Trans. Ind. Informat.*, vol. 15, no. 12, pp. 6407–6414, Dec. 2019.

[27] Z. Ye *et al.*, "Reliability analysis for series manufacturing system with imperfect inspection considering the interaction between quality and degradation," *Rel. Eng. Syst. Saf.*, vol. 189, pp. 345–356, Sep. 2019.

[28] M. S. J. Ameli, J. Arkat, and F. Barzinpour, "Modelling the effects of machine breakdowns in the generalized cell formation problem," *Int. J. Adv. Manuf. Technol.*, vol. 39, no. 7-8, pp. 838–850, Nov. 2008.

[29] Q. Zhai, L. Xing, R. Peng, and J. Yang, "Multi-valued decision diagram-based reliability analysis of k-out-of-n cold standby systems subject to scheduled backups," *IEEE Trans. Rel.*, vol. 64, no. 4, pp. 1310–1324, Dec. 2015.

[30] Y. Mo *et al.*, "MDD-based performability analysis of multi-state linear consecutive-k-out-of-n: F systems," *Rel. Eng. Syst. Saf.*, vol. 166, pp. 124–131, Oct. 2017.

[31] X. Si, C. Hu, Q. Zhang, and T. Li, "An integrated reliability estimation approach with stochastic filtering and degradation modeling for phased-mission systems," *IEEE Trans. Cybern.*, vol. 47, no. 1, pp. 67–80, Jan. 2017.

[32] Z. P. Xu *et al.*, "Reliability assessment of multi-state phased-mission systems by fusing observation data from multiple phases of operation," *Mech. Syst. Signal Process.*, vol. 118, pp. 603–622, Mar. 2019.

[33] G. J. Wang, R. Peng, and L. D. Xing, "Reliability evaluation of unrepairable k-out-of-n: G systems with phased-mission requirements based on record values," *Rel. Eng. Syst. Saf.*, vol. 178, pp. 191–197, Oct. 2018.

[34] Y. Chen, Y. Y. Li, and R. Kang, "Reliability analysis of MS-PM system based on failure mechanism accumulation method," *IEEE Access*, vol. 6, pp. 45707–45714, 2018.

[35] S. M. Ross, *A First Course in Probability*, 9 ed. London, U.K.: Pearson, 2014.

[36] Bryant, "Graph-based algorithms for Boolean function manipulation," *IEEE Trans. Comput.*, vol. C-35, no. 8, pp. 677–691, Aug. 1986.

[37] L. Xing and Y. Dai, "A new decision-diagram-based method for efficient analysis on multistate systems," *IEEE Trans. Dependable Secure Comput.*, vol. 6, no. 3, pp. 161–174, Jul. 2009.

[38] M. Savsar, "Reliability analysis of a flexible manufacturing cell," *Rel. Eng. Syst. Saf.*, vol. 67, no. 2, pp. 147–152, Feb. 2000.

[39] K. Das, "A comparative study of exponential distribution vs Weibull distribution in machine reliability analysis in a CMS design," *Comput. Ind. Eng.*, vol. 54, no. 1, pp. 12–33, Feb. 2008.

[40] K. Das, R. S. Lashkari, and S. Sengupta, "Machine reliability and preventive maintenance planning for cellular manufacturing systems," *Eur. J. Oper. Res.*, vol. 183, no. 1, pp. 162–180, Nov. 2007.

Zhenggeng Ye (Student Member, IEEE) received the B.S. degree in mechanical engineering from the Henan University of Science and Technology. Luoyang, China, in 2012, and the M.S. degree in mechanical engineering from Jilin University, Changchun, China, in 2015. He is currently working toward the Ph.D. degree in management science and engineering with Northwestern Polytechnical University, Xi'an, China.

Since 2019, he has been a Visiting Scholar with Complex Systems Monitoring, Modeling and Control Laboratory, Harold and Inge Marcus Department of Industrial and Manufacturing Engineering, Pennsylvania State University (University Park), State College, PA, USA. His research interests include manufacturing system modeling, analysis and optimization.

Zhiqiang Cai (Member, IEEE) received the B.S. degree in aircraft design and engineering and the M.S. and Ph.D. degrees in management science and engineering from Northwestern Polytechnical University (NPU), Xi'an, China, in 2003, 2006, and 2010, respectively.

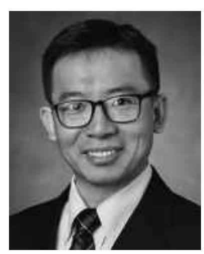
He is currently a Professor of industrial engineering with the School of Mechanical Engineering, NPU. He has authored or coauthored more than 30 academic papers and articles in journals and conferences in the past five years. His research interests include reliability modeling, importance measures, maintenance management, and decision-making support.

Shubin Si (Senior Member, IEEE) received the B.S. and M.S. degrees in mechanical engineering and the Ph.D. degree in management science and engineering from Northwestern Polytechnical University (NPU), Xi'an, China, in 1997, 2002, and 2006, respectively.

He is currently a Professor of industrial engineering with the School of Mechanical Engineering, NPU. He has authored or coauthored more than 60 academic papers and articles in journals and conferences in the past five years. He also headed and participated in seven government supported foundations and more than ten enterprise-supported projects. His research interests include importance measures, system reliability optimization, and fault diagnosis.

Shuai Zhang received the B.S. and M.S. degrees in mechanical engineering from the Northwestern Polytechnical University (NPU), Xi'an, China, in 2005 and 2008, respectively.

She is currently an Associate Professor of industrial engineering with the School of Mechanical Engineering, NPU. Her research interests include complex system reliability, decision diagram modeling, and importance measures.



Hui Yang (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical and computer engineering from the China University of Mining and Technology, Beijing, China, in 2002 and 2005, respectively, and the Ph.D. degree in industrial engineering and management from Oklahoma State University, Stillwater, OK, USA, in 2009.

He is currently an Associate Professor in industrial and manufacturing engineering with the Pennsylvania State University, University Park, PA, USA. His research interests include sensor-based modeling and analysis of complex systems for process monitoring, process control, system diagnostics, condition prognostics, quality improvement, and performance optimization.

Dr. Yang's research program is supported by National Science Foundation (NSF), NSF CAREER award, NSF center for e-Design, NSF Center for Healthcare Organization Transformation, National Institute of Standards and Technology, Lockheed Martin, Susan Koman Cancer Foundation, and Institute of Cyberscience. He is the President during 2017–2018 of Data Analytics and Information Systems Society of Institute of Industrial and Systems Engineers (IISE), the President during 2015–2016 of Quality, Statistics and Reliability Society of Institute for Operations Research and the Management Sciences (INFORMS), and the Program Chair of 2016 Industrial and Systems Engineering Research Conference. He is also an Associate Editor for IISE Transactions, IEEE Journal of Biomedical and Health Informatics, IEEE Transactions on Automation Science and Engineering, and *Quality Technology and Quality Management*.