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Dynamic Modeling Method of Mission Reliability of a Multi-State Manufacturing System With Multiple Production Lines

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ABSTRACT Mission reliability could systematically characterize the running state of a manufacturing system and the rationality of production task setting in advance. However, few studies can realize the mission reliability modeling, which integrates production scheduling based on fully considering the complexity, dynamics, and multi-state characteristics of a manufacturing system. Thus, a dynamic method for modeling the mission reliability of a multi-state manufacturing system with multiple production lines is proposed in this paper. First, the multi-state characteristic of manufacturing systems operation is analyzed. On this basis, considering the composition of manufacturing systems, the connotation and modeling mechanism of the mission reliability of manufacturing systems are proposed. Second, combining the discretization of machine performance states and dynamic continuity of the performance degradation process, the dynamic modeling method of multi-state machine performance and buffer usage are respectively discussed. The transfer evolution of task demands in the production line is analyzed, and the decomposition method of task scheduling and load mapping in multiple production lines is provided. Third, considering the characteristics of multiple production lines and the buffer of a manufacturing system, taking production tasks as the core and integrating production scheduling, a modeling method for the mission reliability of manufacturing systems is proposed. Finally, the effectiveness of the proposed approach is verified using a case study on the modeling of the mission reliability of a manufacturing system of aerospace parts.

INDEX TERMS Mission reliability, dynamic modeling, multi-state, manufacturing system, multiple production lines.

I. INTRODUCTION

As individualized and small batch production modes become popular, manufacturing systems are gradually and increasingly required to be flexible, and the manufacturing process continuously incorporates the characteristics of multi-threading and multi-task flow. The RQR (i.e., Reliability-Quality-Reliability) chain proposed by He *et al.* [1] reveals that the reliability of a machine is the root cause of manufacturing quality deviations and product quality defects. The healthy operation of a machine is the premise of process quality control and the output of high-reliability products. With the introduction of the intelligent manufacturing concept represented by ''predictive production'', considering a dynamic production process as the core, integrating the various components of manufacturing systems and establishing a scientific and comprehensive model of manufacturing system reliability have become popular research topics. Reliability modeling results that fully reflect the operating state of a system can also provide a reference for precise control and refined management of the manufacturing process [2]. Currently, there are many studies in the field of modeling the reliability of manufacturing systems, and these studies have also experienced from static to dynamic to multi-state development.

The static reliability modeling method with a reliability block diagram [3] as the primary tool ignores the influences of man, machines, materials, methods, environment,

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and measurement involved in manufacturing systems. It regards the manufacturing system as a simple combination of machines and integrates the predicted results of machine failure to represent the reliability of the system. Therefore, it does not have the scientific practicability to provide an accurate basis for all types of production decision-making activities.

With the disadvantages of static reliability modeling gradually exposed, dynamic reliability modeling that considers factors such as sequence, time, conversion rate, and failure criteria in the process of fault propagation, has attracted the attention of many scholars. A variety of dynamic methods for reliability analysis have been formed [4], [5] and have been widely used in manufacturing systems [6], [7]. Based on the dynamic reliability modeling, Yemane and Colledani [8] fully considered the influence of information uncertainty, and proposed an approach for the performance evaluation of unreliable manufacturing systems that considers uncertain machine reliability estimates. However, its essence is still to solve the reliability problem at the level of machine failure around ''performance degradation''.

An intelligent manufacturing system is a typical multi-state system [9], [10]. Due to the complex function and structure of manufacturing system, the binary state reliability theory based on the criteria of normal function and fault cannot effectively reflect a system's actual state, nor can it satisfy the reliability evaluation requirements of a complex manufacturing system. The analysis of the reliability of multi-state systems based on general generating functions [11], a stochastic process method [12], and Monte-Carlo simulation [13] has become a significant branch in the system reliability field. On the one hand, the multi-state reliability analysis method further improves the ''performance degradation'' at the machine level, and, on the other hand, provides a possible approach to advance the reliability assessment based on the structural composition of systems.

As the understanding of the complexity of manufacturing systems deepens, many scholars realize that the reliability of systems cannot be expressed as the integration of the reliability of a single machine [14], [15]. The reliability of manufacturing systems should be oriented to their operational mechanism and functional characteristics, with the dynamic production process as the core, and their components should be integrated. Fortunately, some scholars have attempted to interpret the reliability of manufacturing systems for system functional characteristics and not only from machine failure. For example, Chen and Jin [16] propose that the degradation of component reliability affects the stability of a manufacturing process, and subsequently affects product quality, and establish a correlation model between product quality and component reliability. Ye *et al.* [17] extended it further and thought that the imperfect inspection usually leads to unreliable quality judgments, cause the propagation of unqualified products, and aggravate the degradation of downstream machines, on this basis, they proposed a method of reliability analysis for series manufacturing system. Zhang *et al.* [18] proceeded from the purpose of manufacturing system functions; regarding the formation of product quality in the manufacturing process as the research object, they establish a reliability model of manufacturing systems from the perspective of the process. However, the above studies only focus on product quality and machine performance, fail to cover the whole factors of dynamic operation of a manufacturing system, and do not consider key issues such as buffer effect and multi-state characteristics, which cannot predict the operation state of the whole system. Han *et al.* [19] considered the dynamic operation of manufacturing systems, and used Dempster Shafer (D-S) evidence theory to quantify data from different sensor groups for diagnosing the health state of manufacturing systems. The research draws on the idea of mission reliability modeling, but does not realize the quantitative evaluation of mission reliability. Lin *et al.* [20] and Lin and Chang [21] regard the manufacturing system as a stochastic-flow network, introduce customer demand into the system reliability modeling, and quantify reliability by the ability of machine performance to satisfy customer demand. However, the static analysis of discrete machine performance states and the corresponding probability based on historical statistical data do not conform to the dynamic nature of a system operation process, which limits the application of this method in various production decisions. Similarly, Chen *et al.* [22] proposed the operation mechanism of the fuzzy multi-state manufacturing system of a single series production line, and established the ESFN model, which emphasized the dynamic transfer between states, but ignored the influence of the dynamic performance degradation on the multi-state characteristics.

To realize the unified modeling of dynamic and multi-state characteristics of manufacturing system mission reliability, the inherent characteristics of multiple production lines in the manufacturing system, and the influence of buffers on manufacturing processes are considered, and the connotation of the mission reliability of manufacturing systems is analyzed from the perspective of system engineering. The modeling mechanism of mission reliability is clarified based on the mode of flexible multiple production lines and the uncertainty of the buffer zone on the production process. On this basis, considering the inherent multi-state characteristics and dynamics of manufacturing processes, a dynamic modeling method of mission reliability for a multi-state manufacturing system with buffers and multiple production lines is proposed, and the validity and advancement of the method proposed in this paper are validated by an example of a manufacturing system.

In comparison with previous studies on reliability modeling for a manufacturing system, the main contributions of this study are as follows:

1. Combined with the composition of the manufacturing system, the characteristics of multi-state and dynamic coexistence in the manufacturing process are analyzed innovatively, and the modeling mechanism of the manufacturing system mission reliability is given by the integrating task scheduling process.

2. Based on the multi-state reliability theory and dynamic reliability modeling method, the discrete representation method of machine performance state (including buffer usage state) and the dynamic continuity modeling method of performance degradation process are presented, and the unified modeling of multi-state and dynamic characteristics is realized.

3. Considering the production mode of multiple production lines and buffers in manufacturing systems, a refined dynamic modeling method for mission reliability is proposed, which enables the mission reliability index to guide the production scheduling, maintenance, and other production decisions.

The remainder of the paper is organized as follows. Section 2 explains notations and problem description. Section 3 presents the modeling methods of four related basic models. Section 4 discusses the modeling methods of mission reliability. Section 5 introduces a case study, and Section 6 provides the conclusions.

II. NOTATIONS AND PROBLEM DESCRIPTION

A. NOTATIONS

e	A variable related to machine performance
p_x	A constant that represents the proportional relationship between the frequency of each failure mode
S_x	Production capacity state which related to the failure type of equipment (x=1,2,3,…,M)
ep_x	The probability that the machine in processing capacity state S_x
t	Running time of equipment
τ'	The length of downtime caused by a single planned maintenance
r	The number of planned maintenance activities in time period[0, t]
$\lambda(t)$	Failure rate function
τ	Downtime expectation caused by a single failure
$\boldsymbol{B}$	The buffer zone in the production line
$b_{i,i+1}$	The buffer zone between Machine_i and Machine_{i+1}
$\varsigma_{(i,i+1)}$	the capacity of buffer $b_{i,i+1}$
$S_{x(j,i)}$	The production capacity of ith machine of production line j
$\rho^1_{(j,i)}$	The production qualification rate of ith machine of production line j
$B_{j(i,i+1)}$	Buffer usage
d	Production task demand
$O_{j,\max}$	The maximum output of the j production line under full load
ρ^2_r	The probability that Machine_r outputs unqualified products in the reworking process
B^{I1}_i	The minimum input load to meet task requirements of each machine
B^I_i	The minimum processing load to meet task requirements of each machine
γ	A binary parameter indicating whether there is rework operation
$S_{\partial(j,i)}$	Minimum capacity requirements to satisfy the processing load
R	The buffer is empty or partially empty
F	The buffer is blocked

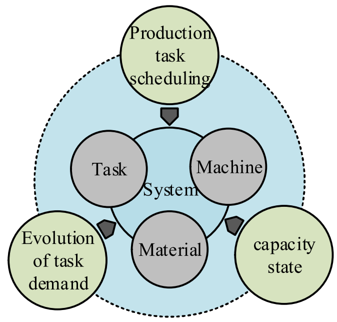

FIGURE 1. Manufacturing system composition and reliability modeling mechanism.

B. PROBLEM DESCRIPTION AND ASSUMPTIONS

A manufacturing system is a dynamic input-output system that converts raw materials into products or semi-finished products as required. The direct service object is the production task. Therefore, modeling the manufacturing system should generally include three parts: production tasks, machines, and materials, as shown in Figure 1.

As Figure 1 shows, without considering the role of human beings, the physical layer of a manufacturing system consists of machines (including buffers), tasks, and materials. Because the manufacturing system has the characteristics of multiple production lines, the tasks here include not only the production task requirements, but also the task scheduling between multiple production lines. Therefore, the corresponding model layer consists of a capacity state model, production task scheduling, and task evolution model.

Manufacturing system is a multi-state system, the multi-state characteristics of the manufacturing system are mainly reflected in the organic combination of multi-state characteristics exhibited by its constituent elements: the multi-states of product quality, system composition structure caused by the variable tasks, and machine performance. To simplify the analysis of the product quality state, this paper divides it into three categories: qualified, unqualified returnable, and scrapped. The multi-state characteristic of the system component structure is the inherent characteristic of a flexible manufacturing system. It mainly emphasizes that the evaluation of the system's operating state should analyze the corresponding production line and machine according to the specific task rather than each component of the whole system. Multi-state characteristics of machine performance (including buffers) are caused by many factors, including tasks, materials, and operational states of the machine. Therefore, it is the key to the analysis of multi-state characteristics of manufacturing systems.

In the manufacturing process, the machine often operates under different processing loads and environments for various tasks. To evaluate machine performance in combination with task demands, we defines the production capacity of a machine as the number of work-in-progress (WIP) processed in a unit time. However, a manufacturing system has the characteristics of a complex structure, various types of faults, variable production tasks, and a lack of single-sample data. The quantification of the performance states of a machine is often uncertain. Therefore, this paper uses the form of interval to represent the performance state of a machine. Interval division is result oriented, that is, converting the downtime caused by repair activities corresponding to various types of faults or defects into the loss of production capacity of a machine under a given production task activity. For example, when a production task is given, and the production capacity of the machine in good condition is 300 pieces/day, the active multi-state characteristics are as follows: According to the influence of each fault artificially, dividing the production capacity of the machine in the form of intervals $S_x = [0, 20, 40, \ldots, 100, \ldots, 300]$, where 20 indicates that the production capacity state is at (0, 20), and the corresponding probability P_x indicates the possibility that machine performance is in this state at a specific time, which is a direct manifestation of passive multi-state characteristics.

Based on the above analysis, this paper focuses on the composition and functional characteristics of manufacturing system, and the dynamic and multi-state characteristics of manufacturing system. The mission reliability of a manufacturing system can be generalized as its ability to complete the export qualified products of a production task under specified conditions and within a specified time. The composition of the manufacturing system shown in Figure 1 indicates that the mission reliability modeling process involves production task scheduling, the transfer and evolution of assigned tasks among machines in each production line, and the capacity state of each machine and buffer.

The manufacturing system studied in this paper does not have too strict restrictions on the manufacturing environment and scale. It applies to a traditional manufacturing system for mass production. The reliability-modeling method proposed in this paper is established based on the following assumptions:

1. Each machine in a manufacturing system is independent in physical composition, and the inspection station is reliable; the inspection process would not damage any WIP or products.

2. Only qualified products can enter the downstream workstation, and defective WIPs can only be reworked once. If they are not qualified after the rework, they are designated as scrap.

3. The proportional relationship between the probabilities of various types of faults occurring at a time is constant, and the repair time after each failure occurs is independent of the degradation in performance or running time of a machine.

III. MODEL BUILDING

A. DYNAMIC MODELING OF MULTI-STATE MACHINE PERFORMANCE

A manufacturing system and its machines are often in the process of continuous degradation as they operate, accompanied by a variety of random failures. Currently, the fault rate $\lambda(t)$ is commonly used to express the performance state of a machine. Using this expression, the operation state of machines is naturally divided into two forms: normal and fault. Expressing the performance state of a machine with failure rate $\lambda(t)$ will lead to the loss of a large amount of effective information, which hinders the application value of the failure rate, the critical machine performance information in actual production.

Based on the multi-state reliability theory, the downtime caused by various types of faults is transformed into the production capacity loss, and the performance state of a machine is then divided into a finite discrete level S_x from the ideal state to complete fault, which can be written as the following set form.

$$\boldsymbol{S_x} = [S_1, S_2, S_3, \ldots, S_x, \ldots, S_M], \tag{1}$$

where $x = M$ is the best working state, $x = 1$ is the complete failure state, and the corresponding state probability P_x can be expressed as the following set form.

$$\boldsymbol{P_x} = [ep_1, ep_2, ep_3, \ldots, ep_x, \ldots, ep_M], \tag{2}$$

where p_x is a constant that represents the proportional relationship between the frequency of each failure mode, and e is a variable related to machine performance. Because each production capacity state of a machine is an independent and mutually exclusive event, $\sum_{x=1}^{M} ep_x = 1$.

The definition of availability is the degree that a product is in a working or usable state at a specific inspection time, and can be expressed as the ratio of the production capacity loss of a machine to the production capacity under perfect state; also, the availability index is often quantified by the ratio of the time that the system can operate generally to the total operating time of the system; hence, it can be expressed as.

$$\sum_{x=1,2\cdots M} \frac{ep_x\left(S_M - S_x\right)}{S_M} = \frac{\tau \int_0^t \lambda\left(t\right) dt + r\tau'}{t}, \tag{3}$$

where $\int_0^t \lambda\left(t\right) dt$ indicates the expectation of the number of failures of a machine in time period [0, t]; τ' indicates the length of downtime caused by a single planned maintenance; r is the number of planned maintenance activities in time period [0, t]; when no maintenance activity is planned, $r = 0$;and τ indicates the expectation of downtime caused by a single failure, whose value can be obtained based on the proportion of different failure modes (δ_e) and the corresponding downtime (t_e^r), $\tau = \sum_{e=1}^{U} \delta_e t_e^r$.

TABLE 1. All possible values of $B_{j(i,i+1)}$.

Upstream workstation (Machine$_{(j,i)}$)			Downstream workstation (Machine$_{(j,i+1)}$)			
			$S_{1(j,i+1)}=0$	$S_{2(j,i+1)}$	$\cdots$	$S_{M_{j,i+1}(j,i+1)}$
Capacity	Output	Probability	$ep_{1(j,i+1)}$	$ep_{2(j,i+1)}$	$\cdots$	$ep_{M_{j,i+1}(j,i+1)}$
$S_{1(j,i)}=0$	$S_{1(j,i)}\rho^1_{(j,i)}$	$ep_{1(j,i)}$	$S_{1(j,i)}\rho^1_{(j,i)}-S_{1(j,i+1)}$	$S_{1(j,i)}\rho^1_{(j,i)}-S_{2(j,i+1)}$	$\cdots$	$S_{1(j,i)}\rho^1_{(j,i)}-S_{M_{j,i+1}(j,i+1)}$
$S_{2(j,i)}$	$S_{2(j,i)}\rho^1_{(j,i)}$	$ep_{2(j,i)}$	$S_{2(j,i)}\rho^1_{(j,i)}-S_{1(j,i+1)}$	$S_{2(j,i)}\rho^1_{(j,i)}-S_{2(j,i+1)}$	$\cdots$	$S_{2(j,i)}\rho^1_{(j,i)}-S_{M_{j,i+1}(j,i+1)}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$S_{M_{j,i}(j,i)}$	$S_{M_{j,i}(j,i)}\rho^1_{(j,i)}$	$ep_{M_{j,i}(j,i)}$	$S_{M_{j,i}(j,i)}\rho^1_{(j,i)}-S_{2(j,i+1)}$	$S_{M_{j,i}(j,i)}\rho^1_{(j,i)}-S_{2(j,i+1)}$	$\cdots$	$S_{M_{j,i}(j,i)}\rho^1_{(j,i)}-S_{M_{j,i+1}(j,i+1)}$

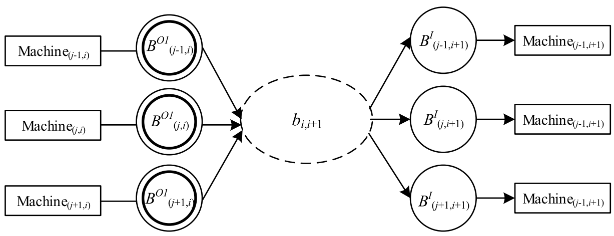

FIGURE 2. A buffer station among workstations.

Based on Eq. (3), the expression of the parameter variable related to performance state can be obtained.

$$e=\frac{S_M\left(\tau\int_0^t\lambda(t)\,dt+r\tau'\right)}{t\sum\limits_{x=1,2\cdots M}p_x\left(S_M-S_x\right)}\tag{4}$$

B. DYNAMIC MODELING OF MULTI-STATE BUFFER CAPACITY

Let **B** represent the buffer zone in the production line and $b_{i,i+1}$ represents the buffer zone between Machine$_i$ and Machine$_{i+1}$. Without losing generality, take three production lines as an example, as shown in Figure 2; buffer $b_{i,i+1}$ are used to store qualified WIPs produced from Machine$_{(j-1,i)}$, Machine$_{(j,i)}$, and Machine$_{(j+1,i)}$, and then respectively deliver them to Machine$_{(j-1,i+1)}$, Machine$_{(j,i+1)}$, and Machine$_{(j+1,i+1)}$. Please note that setting buffer stations between every pair of workstations is not necessary. That is, the buffer volume is zero if no buffer station set exists between workstations.

Assuming the capacity of buffer $b_{i,i+1}$ is $\varsigma_{(i,i+1)}$, according to Eq. (1), the production capacity of each machine can be expressed as $S_{x(j,i)}$, the production qualification rate as $\rho^1_{(j,i)}$, and the expected output as $S_{x(j,i)}\rho^1_{(j,i)}$. The possible production capacity of Machine$_{(j,i)}$ can be expressed as $\left\{S_{1(j,i)},S_{2(j,i)},S_{3(j,i)},\cdots,S_{M(j,i)}\right\}$, and the corresponding probability is $\left\{ep_{1(j,i)},ep_{2(j,i)},ep_{3(j,i)},\cdots,ep_{M(j,i)}\right\}$. The difference between the output capacity of Machine$_{(j,i)}$ and the production capacity of Machine$_{(j,i+1)}$ is expressed as $S_{x(j,i)}\rho^1_{(j,i)}-S_{x(j,i+1)}$; if $S_{x(j,i)}\rho^1_{(j,i)}-S_{x(j,i+1)}>0$, the redundant output is stored in the buffer. $B_{j(i,i+1)}$ is set to indicate excess.

$$B_{j(i,i+1)}=\max\left(0,\ S_{x(j,i)}\rho^1_{(j,i)}-S_{x(j,i+1)}\right)\tag{5}$$

Because the buffer may store the same product from different production lines, if there are m production lines, the total amount of excess is $\sum\limits_{j=1}^{m}B_{j(i,i+1)}$, and its value represents the usage of the buffer. Due to the multi-state characteristic of machine performance, $B_{j(i,i+1)}$ will present multiple values; hence, $B_{j(i(x_i),i+1(x_{i+1}))}$ is set to represent the usage under the production capacity state $(S_{x_i(j,i)},S_{x_{i+1}(j,i+1)})$, where $x_i=1,2,\cdots,M_{j,i}$ and $x_{i+1}=1,2,\cdots,M_{j,i+1}$. Therefore, the probability of buffer usage $\sum\limits_{j=1}^{m}B_{j(i(x_i),i+1(x_{i+1}))}$ is $\sum\limits_{j=1}^{m}ep_{x_i(j,i)}ep_{x_{i+1}(j,i+1)}$. All the possible values of $B_{j(i,i+1)}$ are provided in Table 1. $B_{j(i,i+1)}$ is the redundant output stored in the buffer, quantified by the difference between the output capacity of the upstream machine $(S_{x(j,i)}\rho^1_{(j,i)})$ and the production capacity of the downstream machine $(S_{x(j,i+1)})$. Note that if $S_{x(j,i)}\rho^1_{(j,i)}-S_{x(j,i+1)}<0$, $B_{j(i,i+1)}=0$. Table 2 further indicates the corresponding probabilities of $B_{j(i,i+1)}$. It is quantified by the product of the probability that the output capacity of the upstream machine is $S_{x(j,i)}\rho^1_{(j,i)}$ and the probability that the production capacity of the downstream machine is $S_{x(j,i+1)}$.

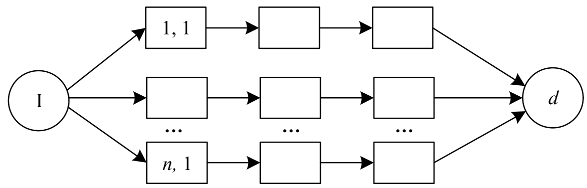

FIGURE 3. n identical production lines in parallel.

C. TASK SCHEDULING BETWEEN MULTIPLE PRODUCTION LINES

For a given manufacturing system production task d, assume that the manufacturing system is composed of n serial production lines, as shown in Figure 3, the result of the production task assignment can be expressed as $(d_1,\ d_2,\cdots,d_n)$.

TABLE 2. Corresponding probabilities of $B_{j(i,i+1)}$.

Upstream workstation (Machine$_{(j,i)}$)			Downstream workstation (Machine$_{(j,i+1)}$)			
			$S_{1(j,i+1)}=0$	$S_{2(j,i+1)}$	$\cdots$	$S_{M_{j,i+1}(j,i+1)}$
Capacity	Output	Probability	$ep_{1(j,i+1)}$	$ep_{2(j,i+1)}$	$\cdots$	$ep_{M_{j,i+1}(j,i+1)}$
$S_{1(j,i)}=0$	$S_{1(j,i)}\rho^1_{(j,i)}$	$ep_{1(j,i)}$	$ep_{1(j,i)}ep_{1(j,i+1)}$	$ep_{1(j,i)}ep_{2(j,i+1)}$	$\cdots$	$ep_{1(j,i)}ep_{M_{j,i+1}(j,i+1)}$
$S_{2(j,i)}$	$S_{2(j,i)}\rho^1_{(j,i)}$	$ep_{2(j,i)}$	$ep_{2(j,i)}ep_{1(j,i+1)}$	$ep_{2(j,i)}ep_{2(j,i+1)}$	$\cdots$	$ep_{2(j,i)}ep_{M_{j,i+1}(j,i+1)}$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$S_{M_{j,i}(j,i)}$	$S_{M_{j,i}(j,i)}\rho^1_{(j,i)}$	$ep_{M_{j,i}(j,i)}$	$ep_{M_{j,i}(j,i)}ep_{1(j,i+1)}$	$ep_{M_{j,i}(j,i)}ep_{2(j,i+1)}$	$\cdots$	$ep_{M_{j,i}(j,i)}ep_{M_{j,i+1}(j,i+1)}$

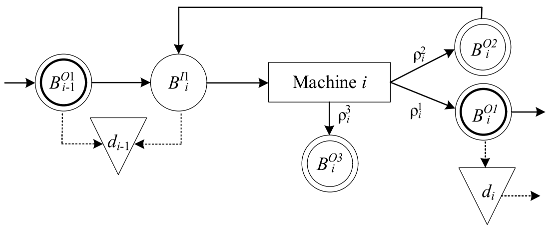

FIGURE 4. Overlapping decomposition of task demand.

Set $O_{j,\max}$ as the maximum output qualified product quantity of the j production line under full load. When scheduling production tasks, the task allocation results should satisfy the following requirements: $d_j \le O_{j,\max}$, and $d_1 + d_2 + \cdots + d_n = d$.

The maximum output quantity of qualified products of each production line is determined as follows.

$$O_{j,\max} = \min\left\{ S_M \prod\nolimits_i^{\rho_i^1} \left(1+\gamma\rho_r^2\right) \middle| \, i \in L_j \right\} \tag{6}$$

where r refers to the machine number with a rework process, when $j \le r$, i.e., the current machine is upstream of Machine$_r$, otherwise $\gamma = 0$; ρ_i^1 refers to the product qualification rate of Machine$_i$; and ρ_r^2 refers to the probability that Machine$_r$ outputs unqualified products in the reworking process.

D. OVERLAPPING DECOMPOSITION AND QUANTITATIVE MODELING OF A TASK LOAD

Select a machine unit j in the manufacturing system as the research object; its operation process is shown in Figure 4. Assume that B_j^I materials can output B_j^{O1} qualified products after processing.

Figure 4 can be described as follows: B_{i-1}^{O1} qualified WIPs ($B_{i-1}^{O1} \ge d_{i-1}$, d_{i-1} is the task demand of Machine$_{i-1}$) produced in the upstream process are delivered to Machine$_i$. After the first processing of Machine$_i$, B_i^{I1} in-process products output $\rho_i^1 B_i^{I1}$ qualified products, and $B_i^{O2} = \rho_i^2 B_i^{I1}$ defective products ($\rho_i^2 = 1 - \rho_i^1$) are generated. After reprocessing, $\rho_i^1 B_i^{O2}$ qualified products are output, while products still unqualified after the second processing are defined as scrap products. The quantitative relationship of this process can be expressed as follows.

$$\begin{pmatrix} B_i^{O2} \\ B_i^{O1} \\ B_i^{O3} \end{pmatrix} = \begin{pmatrix} \rho_i^2 & 0 \\ \rho_i^1 & \rho_i^1 \\ 0 & \rho_i^2 \end{pmatrix} \begin{pmatrix} B_i^{I1} \\ B_i^{I1}\rho_i^2 \end{pmatrix} \tag{7}$$

The minimum input load to meet task requirements of each machine is determined as follows.

$$B_i^{I1} = \frac{d_i}{\rho_i^1\left(1+\gamma\rho_i^2\right)} \tag{8}$$

The minimum processing load is not affected by rework, which is expressed as $B_i^I = \frac{d_i}{\rho_i^1}$. when there is rework operation, $B_i^I = B_i^{I1}$.

The quantitative relationship between the processing load and task requirements can be established.

$$d_{i-1} = \frac{B_i^I}{1+\gamma\rho_i^2} \tag{9}$$

where γ is a binary coefficient; when there is rework operation, $\gamma = 1$; otherwise $\gamma = 0$.

If $\gamma = 1$,

$$d_{i-1} = \frac{B_i^I}{1+\rho_i^2} \tag{10}$$

If $\gamma = 0$,

$$d_{i-1} = B_i^I \tag{11}$$

IV. DYNAMIC MODELING OF MISSION RELIABILITY OF A MANUFACTURING SYSTEM WITH MULTIPLE PRODUCTION LINES

According to the connotation of the mission reliability of a manufacturing system, when the current production capacity of the machine satisfies the task load, it is reliable. Therefore, for Machine$_{(j,i)}$, the mission reliability can be expressed as $\Pr\left(S_{j,i} \ge B_{j,i}^{I1}\right)$.

According to the dynamic modeling of multi-state buffer capacity, we can see that the use of buffers mainly depends on the production capacity of upstream and downstream machines, and the distribution probability is affected by the two machines together. Set a set of minimum capacity states as $\left(S_{\partial(j,i)}, \ S_{\beta(j,i+1)}\right)$ to satisfy the task requirements for

$\text{Machine}_{(j,i)}$ and $\text{Machine}_{(j,i+1)}$ in the same production line: $1 \leq \partial \leq M_{j,i}$ and $1 \leq \beta \leq M_{j,i+1}$.

The buffer capacity is $\varsigma_{(i,i+1)}$. When $\sum_{j=1}^{m} B_{j(i,i+1)} \leq \varsigma_{(i,i+1)}$, the buffer is reliable, that is, the buffer usage is less than the maximum buffer capacity limit. For m production lines, let $\mathbf{R}$ indicate that the production capacity $\left(S_{j,i},\ S_{j,i+1}\right)$ empties or partially empties the buffer area $b_{i,i+1}$, if and only if $\sum_{j=1}^{m} B_{j(i,i+1)} \leq \varsigma_{(i,i+1)}$ and $\left(S_{j,i},\ S_{j,i+1}\right) \in \mathbf{R}$. Let $\mathbf{F}$ indicate that the production capacity $\left(S_{j,i},\ S_{j,i+1}\right)$ blocks the buffer area $b_{i,i+1}$. If and only if $\sum_{j=1}^{m} B_{j(i,i+1)} > \varsigma_{(i,i+1)}$, $\left(S_{j,i},\ S_{j,i+1}\right) \in \mathbf{F}$. By deducting unreliable items $\Pr\left(\mathbf{F}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right)$, the reliability of a small system composed of $\text{Machine}_{(j,i)}$, $b_{i,i+1}$, $\text{Machine}_{(j,i+1)}$ can be expressed as follows.

$$\begin{aligned}
&\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} \sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_i(j,i)} ep_{x_{i+1}(j,i+1)}\right] \\
&\quad - \Pr\left(\mathbf{F}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right) \\
&= \prod_{j=1}^{m} \Pr\left(S_{j,i} \geq S_{\partial(j,i)}\right) \\
&\quad \times \Pr\left(\mathbf{R}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right) \\
&\quad \times \prod_{j=1}^{m} \Pr\left(S_{j,i+1} \geq S_{\beta(j,i+1)}\right)
\end{aligned} \tag{12}$$

For a demand pattern $(d_1, d_2, \ldots, d_j, \ldots, d_m)$, the system reliability model can be denoted as follows.

$$\begin{aligned}
&R(d_1, d_2, \ldots, d_j, \ldots, d_m) \\
&= \prod_{j=1}^{m} \prod_{i=1}^{n} \Pr\left(S_{j,i} \geq S_{\partial(j,i)}\right) \\
&\quad \times \prod_{i=1}^{n-1} \Pr\left(\mathbf{R}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right)
\end{aligned} \tag{13}$$

where $\prod_{j=1}^{m} \prod_{i=1}^{n} \Pr\left(S_{j,i} \geq S_{\partial(j,i)}\right)$ indicates the system's mission reliability without considering the impact of a buffer and $\prod_{i=1}^{n-1} \Pr\left(\mathbf{R}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right)$ is the mission reliability of the buffer.

$$\begin{aligned}
&\prod_{i=1}^{n-1} \Pr\left(\mathbf{R}\left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j\right.\right) \\
&= \frac{\Pr\left(\sum_{j=1}^{m} B_{j(i,i+1)} \leq \varsigma_{(i,i+1)} \left|S_{j,i} \geq S_{\partial(j,i)}\ and\ S_{j,i+1} \geq S_{\beta(j,i+1)}\right.\right)}{\prod_{j=1}^{m}\left[\Pr\left(S_{j,i} \geq S_{\partial(j,i)}\right) \Pr\left(S_{j,i+1} \geq S_{\beta(j,i+1)}\right)\right]}
\end{aligned} \tag{14}$$

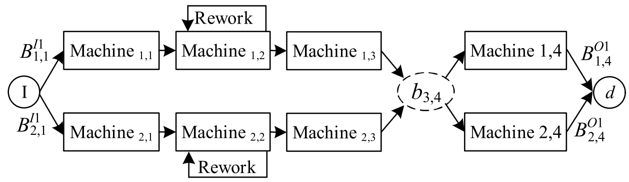

FIGURE 5. Schematic diagram of local process.

V. CASE STUDY

A. BACKGROUND

The effectiveness and advancement of the proposed method are verified through the example of a basic aerospace part manufacturing system. The fundamental part is the engine cylinder head of aerospace special vehicle. Which is exposed to high-pressure gas for a long time and bears high mechanical stress and thermal load. Therefore, the machining accuracy of the cylinder head is required to be high. Due to the requirements of high precision, the complexity of the manufacturing process, and the production mode of multiple production lines, the timely completion of production tasks and the quality of output products have been difficult to be effectively controlled. The processing of the cylinder head involves 13 main processes. Taking one of the critical processes as an example, the process involves two production lines with a total of 8 machines. According to the principle of its processing process, this manufacturing system can be described as a flow shop manufacturing network with four machines for each production line, as shown in Figure 5. According to the production task requirements, $d = 360$ pieces/day.

B. ILLUSTRATED EXAMPLE

The necessary operation data in the production management department were collected, considering the wide application of the Weibull distribution in the failure rate modeling of large mechanical and electrical products. The Weibull distribution was used to fit the trend of the failure rate of a machine, and statistical analysis on the failure maintenance and quality inspection data was performed. The relevant fundamental parameter values were obtained as follows.

According to the historical maintenance data of the machine, the proportional relationship between the occurrence probabilities of each failure mode of each machine was analyzed. The production capacity and probability distribution state of each machine are shown in Table 4.

The maximum output capacity of each production line was determined according to Eq. (6):

$$\begin{aligned}
O_{1,\max} &= \min\{218.93,\ 228.05,\ 190.12,\ 196\} \\
O_{2,\max} &= \min\{273.66,\ 285.06,\ 285.18,\ 235.2\}
\end{aligned}$$

For the above results, the demand patterns were set as $\left(B_{1,4}^{O1},\ B_{2,4}^{O1}\right)$. The setting of task demand patterns should satisfy $B_{1,4}^{O1} + B_{2,4}^{O1} = 360$ under the constraints of $B_{1,4}^{O1} \leq 190.12$ and $B_{2,4}^{O1} \leq 235.2$.

TABLE 3. Parameter value in case.

Parameter	value	Parameter	value	Parameter	value
$\alpha_{1,1}$	3	$\eta_{2,2}$	54	$\tau_{2,4}$	0.25
$\eta_{1,1}$	50	$\alpha_{2,3}$	3.5	$\rho_{1,1}^{1}$	0.96
$\alpha_{1,2}$	2.5	$\eta_{2,3}$	60	$\rho_{1,2}^{1}$	0.98
$\eta_{1,2}$	40	$\alpha_{2,4}$	3	$\rho_{1,3}^{1}$	0.97
$\alpha_{1,3}$	3	$\eta_{2,4}$	47	$\rho_{1,4}^{1}$	0.98
$\eta_{1,3}$	47	$\tau_{1,1}$	0.43	$\rho_{2,1}^{1}$	0.96
$\alpha_{1,4}$	2	$\tau_{1,2}$	0.3	$\rho_{2,2}^{1}$	0.98
$\eta_{1,4}$	62	$\tau_{1,3}$	0.36	$\rho_{2,3}^{1}$	0.97
$\alpha_{2,1}$	3	$\tau_{1,4}$	0.25	$\rho_{2,4}^{1}$	0.98
$\eta_{2,1}$	65	$\tau_{2,1}$	0.3	$b_{3,4}$	60
$\alpha_{2,2}$	3	$\tau_{2,2}$	0.36		

TABLE 4. Production capacity and the probability distribution of each machine.

Machine	Capacity	Probability	Machine	Capacity	Probability
	0	$e_{1,1}$		0	$e_{2,1}$
	60	$e_{1,1}$		75	$e_{2,1}$
1,1	120	$e_{1,1}$	2,1	150	$e_{2,1}$
	180	$2e_{1,1}$		225	$2e_{2,1}$
	240	$1-5e_{1,1}$		300	$1-5e_{2,1}$
	0	$e_{1,2}$		0	$e_{2,2}$
	60	$2e_{1,2}$		75	$e_{2,2}$
1,2	120	$2e_{1,2}$	2,2	150	$e_{2,2}$
	180	$3e_{1,2}$		225	$3e_{2,2}$
	240	$1-8e_{1,2}$		300	$1-8e_{2,2}$
	0	$e_{1,3}$		0	$e_{2,3}$
	50	$1.5e_{1,3}$		60	$2e_{2,3}$
1,3	100	$2e_{1,3}$		120	$2e_{2,3}$
	150	$5e_{1,3}$	2,3	180	$3e_{2,3}$
	200	$1-9.5e_{1,3}$		240	$5e_{2,3}$
				300	$1-13e_{2,3}$
	0	$e_{1,4}$		0	$e_{2,4}$
	50	$2e_{1,4}$		60	$2e_{2,4}$
1,4	100	$2e_{1,4}$	2,4	120	$2e_{2,4}$
	150	$5e_{1,4}$		180	$5e_{2,4}$
	200	$1-10e_{1,4}$		240	$1-10e_{2,4}$

For each demand pattern, the following operations were performed, taking (160, 200) as an example.

1) Determine the minimum processing load of each machine based on Eqs. (7–9).

$B_{1,4}^{I} = 163.27, B_{1,3}^{I} = 168.31, B_{1,2}^{I} = 171.75, B_{1,1}^{I} = 175.40$;

$B_{2,4}^{I} = 204.08, B_{2,3}^{I} = 210.39, B_{2,2}^{I} = 214.69, B_{2,1}^{I} = 219.25$.

2) For each machine, determine the minimum capacity requirements $S_{\partial(j,i)}$ to satisfy the processing load.

$S_{4(1,1)} = 180, S_{4(1,2)} = 180, S_{5(1,3)} = 200, S_{4(2,1)} = 225$; $S_{4(2,1)} = 225, S_{5(2,3)} = 240, S_{5(2,4)} = 240, S_{5(2,4)} = 240$.

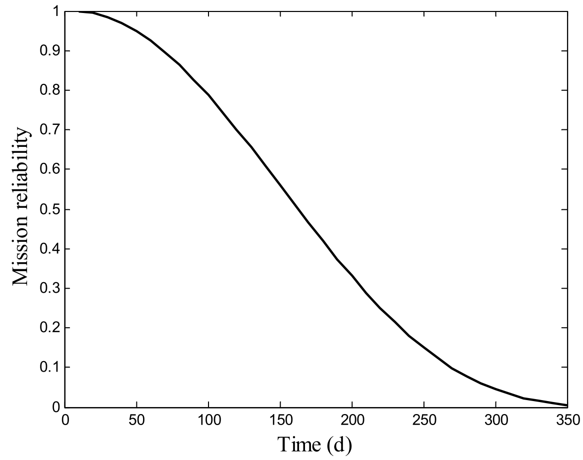

FIGURE 6. Mission reliability curve with demand pattern (160 200).

According to Eq. (14), when $b_{3,4} = 60$, the buffer was reliable for the demand pattern (160 200); hence, the mission reliability can be expressed as $\prod_{j=1}^{2}\prod_{i=1}^{4}\Pr\left(S_{j,i} \geq S_{\partial(j,i)}\right)$. MATLAB was used to complete the relevant calculation and analysis, and the results are shown in the figure below.

C. DISCUSSION

Sensitivity analysis and comparative verification were performed to further verify the effectiveness of the methods proposed in this paper. This paper focused on the unified modeling of the dynamic and multi-state characteristics of the manufacturing system mission reliability, and considered the task scheduling among multiple production lines and the impact of the buffer. The multi-state characteristics were mainly reflected in the use of the multi-state reliability theory to carry out the manufacturing system mission reliability modeling. Therefore, the sensitivity analysis in this paper included the dynamic analysis of task reliability over time, the impact of different task allocation results on mission reliability, and the impact of buffer capacity on mission reliability.

The impact of the operation time t on the changing trend of manufacturing system mission reliability is shown in Figure 6, depicting a monotonous downward trend. Therefore, the following sensitivity analysis mainly analyzed the impact of the results of different task allocations and buffer capacity settings on the mission reliability of the manufacturing system.

Under the total task demand of $d = 360$ pieces/day, the production tasks were allocated to form six task requirements combinations, namely, (170 190), (160 200), (150 210), (140 220), (130 230), and (190 170). The calculation and analysis were conducted under the conditions of $b_{3,4} = 50$ and $b_{3,4} = 60$, and the dynamic mission reliability of the buffer is shown in Figures 7 and 8, respectively.

According to the results shown in Figure 7, when $b_{3,4} = 50$, due to the inherent differences in the production capacity of the upstream and downstream machines in the buffer, that is, the output capacity of the upstream machine

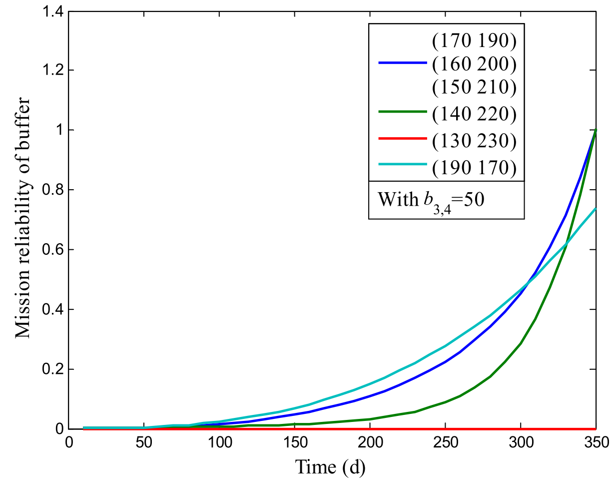

FIGURE 7. Mission reliability of buffer with $b_{3,4} = 50$.

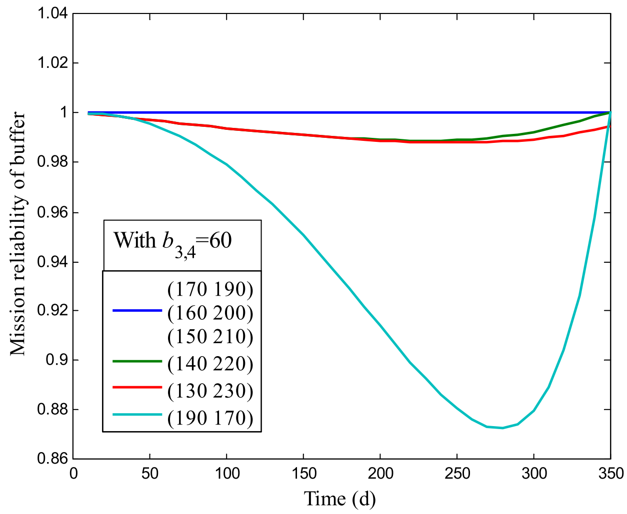

FIGURE 8. Mission reliability of buffer with $b_{3,4} = 60$.

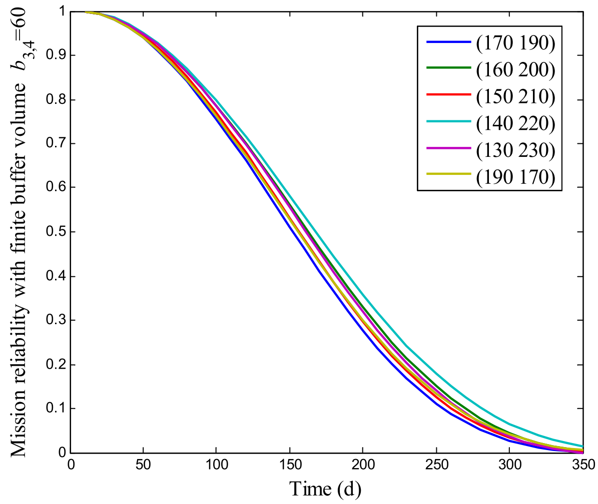

FIGURE 9. Demand patterns and mission reliability with finite buffer volume.

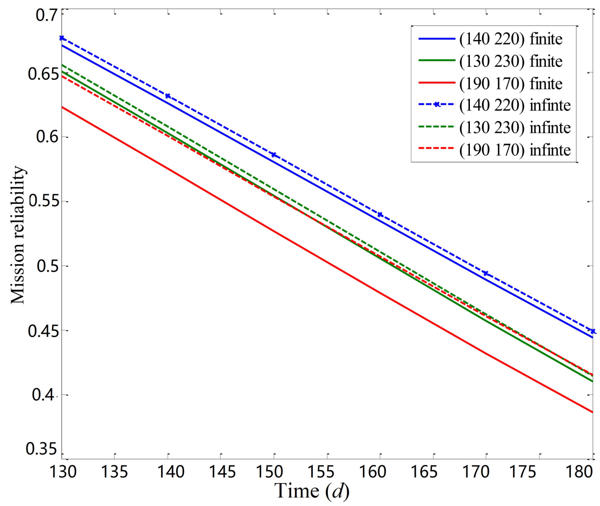

FIGURE 10. Demand patterns and system reliability.

is more likely to be higher than the production capacity of the downstream machine, and the higher value is greater than the buffer capacity, the buffer capacity 50 is difficult to satisfy the production demand; When the performance of machines deteriorates, the probability that the difference between the output capacity of the upstream machine and the production capacity of the downstream machine is greater than the buffer capacity will be reduced, thus the figure shows that when the performance declined, the mission reliability of the buffer gradually increased.

According to the results shown in Figure 8, when $b_{3,4} = 60$, the buffer capacity could adapt to the inherent differences in the production capacity of the upstream and downstream machines. Therefore, when the machine performance was good (i.e., t→0), the mission reliability of the buffer was 1. According to different task allocation results, when a production line is overloaded, the buffer mission reliability will show a trend of decreasing first and then increasing. This is because the performance degradation of the downstream machine is faster than that of the upstream machine. When a load of a single production line is too large, there is a certain probability of full buffer.

The mission reliability of the manufacturing system under different task demand patterns was analyzed, and the results are shown in Figure 9.

According to the analysis results, when the demand pattern was (140, 220), the mission reliability was the highest. Therefore, for the total task demand of d = 360 pieces/day, the production task demand pattern was set to (140, 220) to ensure the system to complete the production task more stably.

Figure 10 compares the reliability modeling results with and without a buffer; it clearly shows that when buffer impact was not considered, the mission reliability was significantly overestimated.

Compared with that in Reference [23], without considering the impact of a buffer, and taking demand pattern (160, 200) as an example, using the method in reference [23], parameter variable e should be a fixed value of statistics in a certain period of time. Then the mission reliability of the manufacturing system should be a constant between 0 and 1, and a straight line is plotted in Figure 6. Therefore, the method proposed in this paper can dynamically evaluate the mission reliability of manufacturing systems. With the production task as the core, according to the impact of degradation of machine performance on the mission reliability, it can scientifically guide the formulation of predictive maintenance strategies. Also, the dynamic method for modeling the mission reliability of a multi-state manufacturing system with multiple production lines proposed in this paper can provide the basis for production scheduling. Therefore, this method can realize the fine control and optimization of a manufacturing process and improve the science of production decisions.

VI. CONCLUSIONS

In this paper, based on system identification of the components of manufacturing systems, a dynamic method to model mission reliability for a multi-state manufacturing system with multiple production lines is proposed. Taking the multi-state characteristic of the manufacturing system operation process as the starting point, and fully mining and using all kinds of production process data (including machine performance data, fault data, maintenance data, production task data, product quality data, etc.) to improve the accuracy of modeling results, the dynamic modeling method of machine performance and buffer usage under multi-state characteristics are discussed respectively, which realizes the unified modeling of the discretization of machine performance state and the dynamic continuity of the performance degradation process. Considering the task scheduling among multiple production lines, the transfer and evolution of production tasks in production lines are analyzed, and the quantitative method of manufacturing system mission reliability is given, which realizes the optimization of production task scheduling by mission reliability.

This method combines the multi-state reliability theory with the dynamic reliability theory. It compensates for the shortcomings of traditional modeling of manufacturing system reliability that cannot reflect the actual operational state of a system and cannot provide a basis for production decisions. It is helpful to realize the fine optimization based on specific production tasks. This method has high pertinence and operability, and can provide a decisive basis for predictive maintenance, production scheduling, and other production decision-making research.

The operation process of manufacturing systems involves many factors such as man, machine, material, method, environment, and measurement. In this paper, some assumptions are made, and the state prediction method based on historical statistical data is adopted. The real-time detection and fusion and update of statistical and historical data are not involved in this paper. For improved portability, two conditions are provided below for future research.

1) Based on the idea of information fusion, using the small sample superposition method, and based on the principle of new information priority, to realize the updating of data information, mining, discovering, and mastering the internal laws of data series, and then modeling

$$
\begin{aligned}
&\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_i(j,i)}ep_{x_{i+1}(j,i+1)}\right]-\Pr\left(\mathbf{F}\left|S_{j,i}\geq S_{\partial(j,i)}\ and\ S_{j,i+1}\geq S_{\beta(j,i+1)}\forall j\right.\right)\\
&=\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]-\Pr\left(\mathbf{F}\left|S_{j,i}\geq S_{\partial(j,i)}\ and\ S_{j,i+1}\geq S_{\beta(j,i+1)}\forall j\right.\right)\\
&=\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]\\
&\quad\times\frac{\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]-\Pr\left(\mathbf{F}\left|S_{j,i}\geq S_{\partial(j,i)}\ and\ S_{j,i+1}\geq S_{\beta(j,i+1)}\forall j\right.\right)}{\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]}\\
&=\prod_{j=1}^{m}\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\times\frac{\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]-\Pr\left(\mathbf{F}\left|S_{j,i}\geq S_{\partial(j,i)}\ and\ S_{j,i+1}\geq S_{\beta(j,i+1)}\forall j\right.\right)}{\prod_{j=1}^{m}\left[\sum_{x_i=\partial}^{M_{j,i}} ep_{x_i(j,i)}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\right]}\times\prod_{j=1}^{m}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_{i+1}(j,i+1)}\\
&=\prod_{j=1}^{m}\Pr\left(S_{j,i}\geq S_{\partial(j,i)}\right)\times\Pr\left(\mathbf{R}\left|S_{j,i}\geq S_{\partial(j,i)}\ and\ S_{j,i+1}\geq S_{\beta(j,i+1)}\forall j\right.\right)\times\prod_{j=1}^{m}\Pr\left(S_{j,i+1}\geq S_{\beta(j,i+1)}\right)
\end{aligned}
$$

the mission reliability, to improve the real-time efficiency and accuracy of modeling results.

2) Considering the accumulation and transmission of product quality deviation in the manufacturing process, the process control characteristics that lead to product quality deviation are introduced into the machine performance model to modify the performance state model.

APPENDIX

A. DERIVATION OF EQUATION (8), (9)

As shown in Figure 4, B_i^{I1} in-process products output $\rho_i^1 B_i^{I1}$ qualified products, and $B_i^{O2} = \rho_i^2 B_i^{I1}$ defective products are generated. After reprocessing, $\rho_i^1 B_i^{O2}$ qualified products are output. Therefore, $B_i^{O1} = \rho_i^1 B_i^{I1} + \rho_i^2 B_i^{I1} \rho_i^1 = \rho_i^1 B_i^{I1}(1+\rho_i^2)$. When there is no rework in the process, $B_i^{O1} = \rho_i^1 B_i^{I1}$. Thus, we introduce a binary element γ to unify the representation, $B_i^{O1} = \rho_i^1 B_i^{I1} + \gamma \rho_i^2 B_i^{I1} \rho_i^1 = \rho_i^1 B_i^{I1}(1+\gamma\rho_i^2)$.

Assume that the task requirement is d_i. $B_i^{O1} \geq d_i$ is needed to meet the task requirement. To obtain the minimum input load of the machine, set $B_i^{O1} = d_i$, thus, $B_i^{I1} = \frac{d_i}{\rho_i^1(1+\gamma\rho_i^2)}$.

The minimum input load $B_i^I = B_i^{I1} + \gamma B_i^{I1} \rho_i^1$, the minimum input load of the downstream machine shall not be less than the output requirements of the upstream machine, that is $d_{i-1} \geq B_i^{I1}$. As a minimum requirement, $d_{i-1} = B_i^{I1}$, thus, $d_{i-1} \geq \frac{B_i^I}{1+\gamma\rho_i^2}$.

B. DERIVATION OF EQUATION (12)

$\prod_{j=1}^{m}[\sum_{x_i=\partial}^{M_{j,i}}\sum_{x_{i+1}=\beta}^{M_{j,i+1}} ep_{x_i(j,i)} ep_{x_{i+1}(j,i+1)}] - \Pr(\mathbf{F}|S_{j,i} \geq S_{\partial(j,i)}$ *and* $S_{j,i+1} \geq S_{\beta(j,i+1)} \forall j)$, as shown at the bottom of the previous page.

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