Machine and Feedstock Interdependence Modeling for Manufacturing Networks Performance Analysis

Zhenggeng Ye, *Student Member, IEEE*, Shubin Si, *Senior Member, IEEE*, Hui Yang, *Senior Member, IEEE*, Zhiqiang Cai, *Member, IEEE*, and Fuli Zhou

***Abstract*—The input of low-quality feedstocks triggers the interdependence between workpiece quality and machine reliability, which will further adversely impact the performance of manufacturing systems. Considering the interconnected manufacturing system structures, our primary goal is to provide an effective method to compute the performance of networked manufacturing systems suffering from machine and low-quality feedstock interdependence. The strength of our work first lies in the model for the compound degradation process of machines and dissemination of low-quality feedstocks, which enables us to construct a response chain to model the interdependence between machines and feedstocks in the manufacturing network. Then, the second strength is the effective algorithm for the computation of route connectivity and quality loss of a manufacturing network based on the interdependence model. A computational experiment shows our models and algorithm can work well for evaluating the operational performance of manufacturing networks.**

***Index Terms*—Interdependence, manufacturing network, performance analysis, quality, reliability.**

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Zhenggeng Ye is with the School of Mechanical Engineering, 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 Department of Industrial and Manufacturing Engineering, Pennsylvania State University, University Park, PA 16802 USA (e-mail: yezhenggeng@outlook.com).

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

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

Fuli Zhou is with the College of Economics and Management, Zhengzhou University of Light Industry, Zhengzhou 450001, China (e-mail: deepbreath329@outlook.com).

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I. Introduction

ADVANCED manufacturing technology breeds more and more high-technology manufacturing equipment with more flexible capabilities, increasing the variety of process routes. Moreover, information technology and cloud manufacturing also enable the integration of goods, people, technology, and information, so that various manufacturing paths can be composed for production. As a result, current manufacturing systems consisting of various machines look increasingly like a complex network (relative to regular structures, such as serial, and parallel ones) [1], posing significant challenges to modeling and analyzing their operational features.

One challenge is the lack of applicable methods to model the interdependency between machine reliability and feedstock quality induced by feedstock propagations, which can be used for the effective analysis of irregular manufacturing networks. The propagation of quality issues and its impact on system performance have been proved, no matter in product lines [2], [3], intelligent manufacturing systems with multiple steps [4], multistage manufacturing process [5], multistate manufacturing systems [6], manufacturing plants [7], or supply chains [8]. In the state of the art, however, precisely modeling interdependencies in manufacturing systems and evaluating the performance of systems with complex structures cannot be realized simultaneously. Due to the increasing complexity of analyzing large-scale irregular manufacturing networks, researchers would like to choose simpler models of machine reliability, such as the Exponential models in manufacturing networks [9] or complex fractal networks [10], which only applies to the constant failure rate of machines. However, when investigating the dynamic reliability of machines, researchers focus mainly on the manufacturing system with simple regular structures or process routes, such as the random variable model [11] and threshold model [12], [13] in serial systems or single-unit systems, the mixture degradation model in serial structures [14], the mixed distribution-function model in serial-parallel structures [15], and the proportional hazard model in serial-parallel multistage manufacturing systems [16]. Also, although an extended stochastic flow network was proposed to model the reliability and quality states of multistate manufacturing systems in [17], the applicability on large-scale irregular manufacturing networks is not fully validated. Therefore, effective quality-reliability models are urgently needed for the performance analysis of manufacturing networks, so that interacting behaviors between machines and feedstocks can be characterized.

Furthermore, a valid algorithm of performance evaluation is critical to performance optimization of an engineering system, such as the algorithm for the group maintenance of production facilities [18], the decision-dependent scenario tree in the maintenance optimization of multicomponent systems [19], and the system reliability measurement in the redundancy allocation [20]. However, the structure complexity and machine-feedstock interdependency of manufacturing networks increase the difficulty in evaluating the performance. Therefore, another challenge is the computation of the dynamic system-level performance of the irregular manufacturing network, which can simultaneously capture the dependence of machine reliability and product quality.

Statistical physics promotes the development of network science and brings various complex-network models, e.g., complex weighted networks [21], fractal networks [22], and interdependent networks [23], [24]. Reliability analysis of networks is one important instrument to evaluate the performance of complex networks in system science, which can be realized by various measures, such as the run time, resilience, and connectivity [25]. For example, Paredes *et al.* [26] proposed an extended counting-based method to approximate the *k*-terminal reliability of the network. Botev *et al.* [27] proposed a connectivity algorithm of the given set of nodes by assuming the link had a given failure probability. By assuming that nodes and edges failed statistically independently with known probabilities, Wang *et al.* [10] provided the all-terminal reliability algorithm of a manufacturing network based on fractal theory. Considering the connectivity of the main network cluster, Li *et al.* [28] defined that the network failed when the number of failed nodes reached the threshold and proposed a reliability algorithm by a voting system.

However, these measures of network performance only considered the complete failure of dependent nodes or links when some elements failed. Therefore, they cannot model the incomplete failure caused by the machine-feedstock interdependency in a manufacturing network. First, this incomplete failure refers to the gradual deterioration of processing quality caused by machine degradation in manufacturing networks. Second, when manufactured nonconforming items flow between machines, they will become feedstocks of subsequent machines. Then, this incomplete failure refers to the deterioration of reliabilities of subsequent machines caused by the low-quality feedstocks. Quality issues of flow elements in manufacturing networks admit the main responsibility for the propagation of turbulence, which leads to dynamic interactions between machines and feedstocks and accelerates machine degradation. Therefore, this article presents the next step to fill this gap to develop a modeling framework and an algorithm for the performance evaluation of irregular manufacturing networks with multiple process routes by considering machine-feedstock interdependency.

The main contributions of this article are summarized as follows.

1) In the perspective of modeling, this article proposes an effective framework to model the interdependence between machine reliability and feedstock quality in manufacturing systems by introducing the stochastic model. This framework extends the machine reliability when processing heterogeneous feedstocks by modeling the compound degradation and failure rate. Further, the production and dissemination of low-quality feedstocks caused by unreliable machines are modeled by the compound nonhomogeneous Poisson process (NHPP). Based on these two models, the interacting chain between machines and feedstocks can be effectively characterized in the irregular manufacturing network.
2) Our developed algorithm shows the effectiveness for evaluating the dynamic system-level performance of the irregular manufacturing network, namely the operational risk under the machine-feedstock interdependence. Through the established model, a three-step algorithm is designed to finish the calculation of real-time route connectivity, which can be utilized to analyze the operation risk of manufacturing networks. Further, by the designed experiment scheme, the time-varying route connectivity and quality loss can be computed to measure the operation risk of irregular manufacturing networks suffering machine-feedstock interdependence.

The rest of this article is organized as follows. Section II presents the structure of manufacturing networks and the problem we will study. Section III details the models about machine-feedstock interdependence. Section IV proposes the measurement of route connectivity and quality loss of the manufacturing network and establishes the corresponding algorithm. Section V provides the experiment scheme for the performance analysis. Section VI gives the performance analysis based on the experiment results. Finally, Section VII concludes this article.

II. Problem Description

A. Network Structure of Manufacturing Systems

In this article, only the acyclic flow of feedstocks is considered, and a manufacturing network with n machines is modeled by a directed acyclic graph $G(V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ is the set of vertices representing machines and $E \subseteq V \times V = \{(i,j)|v_i, v_j \in V \text{and} i \neq j\}$ is the set of directed edges. (i, j) is one directed edge directing from v_i to v_j, representing the traveling direction of flow elements. Here, the weighted adjacency matrix A represents the relation of vertices [29]

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

where $a_{ij} \in [0,1]$ is the weight of directed edges, representing the probability that each flow element in vertex i will flow into vertex j, and each vertex i satisfies $\sum_{j=1}^{n} a_{ij} = 1$.

We define $D_i = \{v_j \mid a_{ij} \neq 0 \text{ for } j = 1, \ldots, n\}$ as the set of subsequent vertices (the downstream neighbor) of the vertex i, and $U_j = \{v_i \mid a_{ij} \neq 0 \text{ for } i = 1, \ldots, n\}$ as the set of previous vertices (the upstream neighbor) of the vertex j. If the vertex i does not have previous vertices, namely $U_i = \emptyset$, the vertex i is one source vertex, denoted as $\text{Source} = \{v_i \mid U_i = \emptyset, i = 1, \ldots, n\}$; similarly, the sink vertex is defined as $\text{Sink} = \{v_i \mid D_i = \emptyset, i = 1, \ldots, n\}$. If a vertex has both previous and subsequent vertices, we call it the intermediate vertex, denoted as $\text{Intermediate} = \{v_i \mid D_i \neq \emptyset \text{ and } U_i \neq \emptyset, i = 1, \ldots, n\}$. Then, the in-degree Id_i of vertex i can be obtained by cardinal numbers of the defined sets U_i, namely $Id_i = |U_i|$.

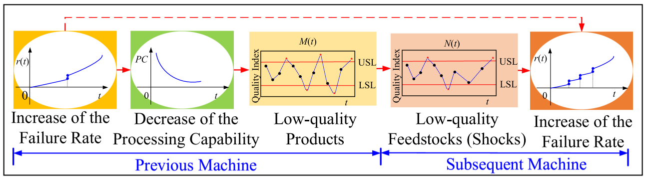

Fig. 1. Machine-feedstock interdependence in a manufacturing network.

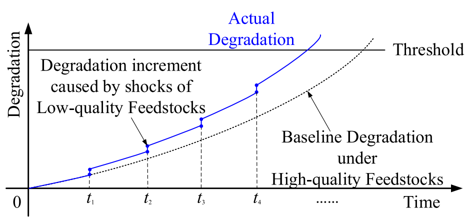

Fig. 2. Degradation trajectory of a machine with heterogeneous quality-level feedstocks.

B. Machine-Feedstock Interdependence

In real-world production, after being processed by the previous machine, the product will become feedstocks with heterogeneous quality and flow into a subsequent refining machine. Accompanied with these flows, failure dependence can occur between connected machines because of shocks from low-quality feedstocks. First, as shown in Fig. 1, the increase of degradation and failure rate in the previous machine will reduce its processing capability, leading to a higher probability of producing low-quality products. Second, after being received by a subsequent machine, low-quality products become its low-quality feedstocks and bring extra turbulence to its degradation, causing random increments of its failure rate in the future. Based on this feature, the interdependence between machine reliability and feedstocks quality is modeled in Section III.

III. Modeling Machine-Feedstock Interdependence

A. Reliability Model of Machines When Processing Heterogeneous Feedstocks

The state of machine deterioration greatly depends on its operating conditions. In the manufacturing industry, the heterogeneity of feedstock quality is one main factor causing the fluctuation of machine operating conditions. In general, a machine will operate with a stable degradation when processing high-quality feedstocks but operate with a serious degradation due to the severe wear and tear when processing low-quality feedstocks. As shown in Fig. 2, it is a possible degradation trajectory of a machine when processing heterogeneous feedstocks, where the machine suffers low-quality feedstocks at times t_1, t_2, t_3, and t_4. We define the stable degradation when processing high-quality feedstocks as the baseline degradation, and the degradation caused by the shock of low-quality feedstocks as the degradation increment.

Considering this compound degradation, we assume a machine has a baseline failure rate $r_b(t)$ during [0, t) when only high-quality feedstocks are processed. Because the Weibull distribution can provide good approximations to machine failure and fit many different failure patterns [30], we use a Weibull distribution to describe the reliability of a machine under the baseline condition, and the baseline failure rate is $r_b(t) = (\beta/\alpha)\cdot(t/\alpha)^{\beta-1}$, where $\alpha\in(0,+\infty)$ and $\beta\in(0,+\infty)$ are scale parameters and shape parameters, respectively. If the machine receives $N(t)$ low-quality feedstocks during [0, t) at the time sequence $\{t_i \,|\, 0 \le t_i \le t,\ i = 1, 2, 3\ldots, N(t)\}$, the actual failure rate $r(t)$ at time t is defined as

$$r(t)=r_b(t)+\sum_{i=1}^{N(t)} \Delta r_i, \tag{2}$$

where Δr_i is the random increment of failure rate caused by the shock of the low-quality feedstock at time t_i. Obviously, due to the baseline nonlinearity and the randomness of failure-rate increments, the actual failure rate will be nonlinear. Also, according to the definition of failure rate, $r(t) = f(t)/(1\text{-}F(t)) = dF(t)/(1\text{-}F(t))$, where $f(t)$ and $F(t)$ are the probability density function (PDF) and cumulative distribution function (CDF) of the machine failure, we can get

$$\begin{aligned} F(t) &= c\cdot e^{-\int r(t)dt} + e^{-\int r(t)dt}\cdot \int r(t)\cdot e^{\int r(t)dt}dt \\ &= 1 + c\cdot e^{-\int (r_b(t)+\sum_{i=1}^{N(t)}\Delta r_i)dt}. \end{aligned} \tag{3}$$

According to the initial condition that $F(0) = 0$ and $r(0) = 0$, we get $c = -1$. Then, we have the actual CDF of the machine failure under compound degradation

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta} - \int \Delta r(t)dt} \tag{4}$$

where $\Delta r(t) = \sum_{i=1}^{N(t)} \Delta r_i$is the accumulative increment of failure rates caused by the shock of low-quality feedstocks, which is one piecewise function, and its integration can be derived by

$$\begin{aligned} \int_0^t \Delta r(s)ds &= \int_0^t \left(\sum_{i=1}^{N(s)} \Delta r_i\right) ds \\ &= \sum_{i=1}^{N(t)} (\Delta r_i\cdot\Delta t_i) = \sum_{i=1}^{N(t)} (\Delta r_i\cdot(t-t_i)) \end{aligned} \tag{5}$$

where $\Delta t_i = t\text{-}t_i$ $(i = 1, 2\ldots, k)$ is the duration of the increment Δr_i. By (3)–(5), we can conclude that our reliability model can reflect both internal and external dependence of machine failures, where the former is caused by the failure-rate increment Δr_i happening before time t and the latter is decided by the $N(t)$ caused by previous machines.

B. Model of the Failure-Rate Increment

Because of the heterogeneity of low-quality feedstocks, the shock will be also heterogeneous. It is reasonable to assume that the failure-rate increment Δr_i $(i = 1,2,\ldots, N(t))$ caused by different low-quality feedstocks is proportional to the quality deviation from benchmarks. In this article, the increment Δr_i in a machine is assumed to be a nonnegative random variable obeying the independent and identical distribution. In real-world engineering, the quality index x of products (for example, the dimension of parts) usually obeys one normal distribution, companied

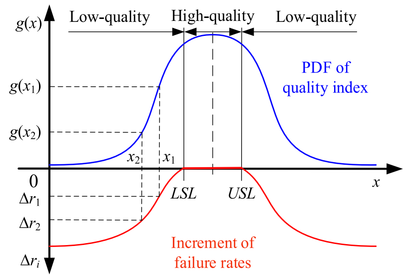

Fig. 3. Relationship between failure-rate increments and quality states of feedstocks.

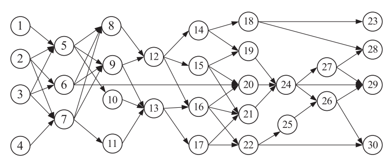

Fig. 4. Manufacturing networks.

with the upper and lower dimensional specification limits (USL and LSL) to define the quality states. As shown in Fig. 3, $g(x)$ is the PDF of one quality index. According to the definition, the increment Δr_i equals zero when x locates inside the high-quality interval [LSL, USL].

Also, considering Taguchi philosophy that quality loss depends on the extent of deviation from the target value [31], it is reasonable to assume Δr_i will increase gradually when x is away from the high-quality interval [LSL, USL]. Therefore, for arbitrary $\Delta r_1 < \Delta r_2$ in Fig. 3, their quality indexes x_1 and x_2 satisfy $g(x_1) > g(x_2)$. In other words, a small failure-rate increment Δr_i will occur more likely than the big one. Obviously, Δr_i obeys a right-skewed distribution. Also, considering the finiteness of the effect from low-quality feedstocks, the random variable Δr_i is assumed to obey the beta distribution beta(a, b) in our research, which is a right-skewed distribution with finite interval when $b > a$ [32].

C. Quality Model Under Machine-Feedstock Interdependence

In real-world production, the number $M(t)$ of low-quality products made by a machine greatly depends on its degradation condition. Also, in engineering fields, the NHPP is one effective mathematical model with a time-varying intensity function $\lambda(t)$ that can depict the number of nonconformities or defects in a repetitive process. Therefore, an NHPP with the following intensity function $\lambda(t)$ is defined to model $M(t)$

$$\lambda(t) = \omega - \varepsilon \cdot e^{-\delta \cdot r(t)} \tag{6}$$

where $t \geq 0$, $\omega > 0$, $\varepsilon > 0$, $\delta > 0$, and $r(t)$ is the actual failure rate of the machine. Here, ω-ε is the initial intensity when the machine is in the perfect condition ($r(t) = 0$), and $\lambda(t)$ locates in [ω-ε, ω). Based on the definition of NHPP [33], the probability that there will be n_m low-quality products made by a machine during [t-h, t) is

$$P\{M(t) - M(t-h) = n_m\}$$
$$= e^{\{-(m(t)-m(t-h))\}} \frac{[m(t) - m(t-h)]^{n_m}}{n_m!} \tag{7}$$

where $m(t) = \int_0^t \lambda(s)ds$ is the average low-quality products during [0, t]. Here, the inspection activity after the machine is assumed to be a binary variable with the probability p to give a wrong judgment about the quality state of low-quality products and the probability 1-p to give the right judgment. Therefore, the low-quality products $M'(t)$ flowing from the machine can be considered as the compound of NHPP $M(t)$ and binomial distribution $B(1, p)$. Then, we can obtain the probability function that there is l ($0 \leq l \leq n_m$) low-quality products flowing to subsequent machines during [t-h, t)

$$\begin{aligned}
&P\{M'(t) - M'(t-h) = l\} \\
&= \sum_{n_m=l}^{\infty} \left[\left(e^{\{-(m(t)-m(t-h))\}} \frac{[m(t) - m(t-h)]^{n_m}}{n_m!} \right) \cdot C_{n_m}^{l} \cdot p^l \cdot (1-p)^{n_m-l} \right] \\
&= e^{\{-(m(t)-m(t-h))\}} \cdot p^l \cdot (1-p)^{-l} \cdot \sum_{n_m=l}^{\infty} \left(\frac{[m(t) - m(t-h)]^{n_m}}{n_m!} \cdot C_{n_m}^{l} \cdot (1-p)^{n_m} \right) \\
&= e^{\{-(m(t)-m(t-h))\}} \cdot p^l \cdot (1-p)^{-l} \cdot \sum_{n_m=l}^{\infty} \left(\frac{[m(t) - m(t-h) \cdot (1-p)]^{n_m}}{l! \cdot (n_m - l)!} \right) \\
&= \frac{e^{\{-(m(t)-m(t-h))\}} \cdot p^l \cdot (1-p)^{-l}}{l!} \cdot [(m(t) - m(t-h)) \cdot (1-p)]^l \cdot \sum_{n_m=l}^{\infty} \left(\frac{[(m(t) - m(t-h)) \cdot (1-p)]^{n_m-l}}{(n_m - l)!} \right) \\
&= \frac{e^{\{-(m(t)-m(t-h))\}} \cdot [p \cdot (m(t) - m(t-h))]^l}{l!} \cdot \sum_{g=0}^{\infty} \left(\frac{[(m(t) - m(t-h)) \cdot (1-p)]^g}{g!} \right) \\
&= \frac{e^{\{-(m(t)-m(t-h))\}} \cdot [p \cdot (m(t) - m(t-h))]^l}{l!} \cdot e^{\{(m(t)-m(t-h)) \cdot (1-p)\}} \\
&= e^{\{-p \cdot (m(t)-m(t-h))\}} \cdot \frac{[p \cdot (m(t) - m(t-h))]^l}{l!}
\end{aligned} \tag{8}$$

where $\sum_0^\infty ([(m(t) - m(t-h)) \cdot (1-p)]^g / (g!))$ is the Taylor series expansion of the exponential function $e^{\{(m(t)-m(t-h)) \cdot (1-p)\}}$. Obviously, the random variable $M'(t)$, the number of low-quality products flowing from a machine during [0, t), obeys another NHPP with the mean $m'(t) = p \cdot m(t)$. According to the defined weight a_{ij} in the network model in Section II-A, feedstocks flowing from vertex i into the subsequent vertex j can be considered as the compound of NHPP $M'(t)$ and binomial distribution $B(1, a_{ij})$. Again, the probability that the number l_{ij} ($0\leq l_{ij}\leq l$) of low-quality feedstocks flow from the vertices i to j during [t-h, t) can be obtained

$$\begin{aligned} &P\{N'_{ij}(t)-N'_{ij}(t-h)=l_{ij}\}\\ &=e^{\{-a_{ij}\cdot p\cdot(m(t)-m(t-h))\}}\cdot\frac{[a_{ij}\cdot p\cdot(m(t)-m(t-h))]^{l_{ij}}}{l_{ij}!} \end{aligned} \tag{9}$$

where the random variable $N'_{ij}(t)$ denotes the number of low-quality feedstocks flowing from the vertices i to j during [0, t), which obeys the other NHPP with the mean $a_{ij}\cdot p\cdot m(t)$. Therefore, for each machine j with the previous vertices U_j, the total number $N_j(t)$ of low-quality feedstocks received from all its previous machines during [0, t) is a compound random variable that consists of $|U_j|$ NHPPs, as shown in

$$N_j(t)=\sum_{i\in U_j}N'_{ij}(t). \tag{10}$$

D. Parameters in the Quality Model

According to the definition of intensity function $\lambda(t)$ in Function (6), for each machine, we have $0\leq\omega-\varepsilon<\lambda(t)<\omega$, namely $0\leq\omega-\varepsilon<m(1)<\omega$, where $m(1)=\int_0^1\lambda(s)ds$is the average low-quality products made during the unit time. Here, denote IF as the flow volume of feedstocks during the unit time in a machine. Therefore, $\omega=\lim\limits_{r(t)\to\infty}\lambda(t)\leq IF$ means that no matter how worse the reliability of the machine is, the intensity of producing low-quality products does not exceed the feedstock flow during the unit time. Therefore, parameters of NHPP in a machine satisfy $\varepsilon\leq\omega\leq IF$.

According to this conclusion, our experiments assume that $\omega=IF$, representing that all processed feedstocks will become low-quality products when machine reliability is worse enough. And assume $\varepsilon=g\times\omega$, where $g\in[0,1]$. Then, we can derive the initial percentage P_{initial} of low-quality products produced by a machine at $t=0$

$$\begin{aligned} &p_{\text{initial}}=\lim_{t\to 0}\frac{\int_0^t\lambda(s)ds}{IF\cdot t}\\ &=\lim_{t\to 0}\frac{\int_0^t\omega-\varepsilon e^{-\sigma\cdot r(s)}ds}{IF\cdot t}=\lim_{t\to 0}\frac{\omega t-\varepsilon\int_0^t e^{-\sigma\cdot r(s)}ds}{IF\cdot t}\\ &=\lim_{t\to 0}\frac{\omega t-g\cdot\omega\int_0^t e^{-\sigma\cdot r(s)}ds}{\omega\cdot t}=1-g\cdot\lim_{t\to 0}\frac{\int_0^t e^{-\sigma\cdot r(s)}ds}{t}=1-g. \end{aligned} \tag{11}$$

Therefore, g is the initial percentage of high-quality products produced by a machine, called the initial quality level of the machine in this article.

IV. Performance Analysis and Algorithm

A. Quality Loss

Based on the proposed model, we measure the quality performance of products and the connectivity between source and sink vertices. Quality loss is defined as the number of low-quality products made by vertices or the network. According to the NHPP model in Section III-C, $M_i(t)$ is the quality loss of machine i during [0, t). Further, the quality loss $Q(t)$ of the network during [0, t) can be obtained. We denote the flow of feedstocks during the unit time in each vertex i as IF_i. Then, we define two indexes to analyze the quality performance of a manufacturing network. The accumulative percentage of low-qualified products P_{cum} (APLP) during [0, t) is defined as the proportion of low-quality products in the network until time t, which is calculated by

$$P_{\text{cum}}(t)=\frac{Q(t)}{\sum\limits_{i=1}^{n}IF_i\times t}=\frac{1}{\sum\limits_{i=1}^{n}IF_i\times t}\cdot\sum_{i=1}^{n}M_i(t). \tag{12}$$

The instantaneous percentage of low-quality product P_{ins} (IPLP) at time t is defined as the proportion of low-quality products manufactured during a given period [t-Δt, t+Δt], as shown in

$$P_{ins}(t)=\frac{1}{\sum\limits_{i=1}^{n}IF_i\times 2\Delta t}\cdot\sum_{i=1}^{n}(M_i(t+\Delta t)-M_i(t-\Delta t)). \tag{13}$$

TABLE I
AAP Algorithm

Algorithm 1: the AAP algorithm

Input: The adjacency matrix B with elements b_{ij}, i, j=1, 2, …, n.
Output: Path set $\boldsymbol{P}$ between source and sink vertices.

1: Identify and classify the source vertices and the sink vertices.
2: **Main-loop:** for all source vertices $v_s\in Source$.
3: For the source vertex v_s, let $L_1=s$, $I=[b_{s1}, b_{s2}, \ldots, b_{sn}]$.
4: Keep record the location $L_2=\{L_2(1), L_2(2), \ldots, L_2(k_2)\}$ of non-zero elements in I as k_2 vectors $[L_1, L_2(i)]$, where k_2 is the number of elements in L_2, and i=1, 2,…, k_2. Set x=2.
5: **Sub-loop**
6: Update $I=I\times B$, $x=x+1$.
7: Keep record the location $L_x=\{L_x(1), L_x(2), \ldots, L_x(k_x)\}$ of non-zero items in I, where k_x is the number of elements in L_x.
8: For i=1, 2,…, $k_{x\text{-}1}$, j=1, 2,…, k_x, if $b_{Lx\text{-}1(i),\,Lx(j)}=1$, based on the recorded vectors, update the vector that has the ending element $L_{x\text{-}1}(i)$ to be a new vector $[L_1, L_2(\cdot), \ldots, L_{x\text{-}1}(i), L_x(j))]$, and keep record them.
9: If $L_x(j)$ is one sink vertex, keep record one path $P=\{L_1, L_2(\cdot), \ldots, L_x(j)\}$.
10: **Until** $I=\mathbf{0}=[0, 0, \ldots, 0]$. (End the sub-loop)
11: **Until** all source vertices are calculated. (End the main-loop)
12: **Return** $\boldsymbol{P}=\{P_1, P_2, \ldots, P_{num}\}$, where num is the number of paths.

B. Connectivity of Routes

In this article, the connectivity is defined as the probability that at least one source vertex and one sink vertex are connected, which is determined by the reliability of vertices. In a manufacturing network, this indicator shows the probability that the system at least has one available process route, which represents the safety of production in a manufacturing network. In other words, the high connectivity means the low risk of production break in a manufacturing network. We denote it as $C(t)=P(W(t)\geq 1)$, where $W(t)$ is the number of connected process routes at time t. Then, one three-step algorithm is proposed for the calculation of this network connectivity, and the first two steps contain two algorithms as given in Tables I and II. Here, Algorithm 1 belongs to one method for enumerating path sets by the information contained in the matrix representation of a network graph [34].

1) *Step* 1: calculate all paths by the adjacency-matrix-based algorithm for paths (AAPs), as given in Table I, where the adjacency matrix B is obtained by replacing all nonzero a_{ij} with 1 in the weighted adjacency matrix A of (1).
2) *Step* 2: eliminate intersections of any two paths to obtain the connectivity function based on the path intersections

TABLE II
PIE ALGORITHM

Algorithm 2: the PIE algorithm
Input: Path sets $\boldsymbol{P}=\{P_1, P_2, \ldots, P_i, \ldots, P_{num}\}$.
Output: The function $C(t)$ of network connectivity.
1: Keep a record $E_1=P_1=\bigcap_{k\in K_1} \boldsymbol{e}_k$, where e_k is the event that vertex k does not fail. Here, K_1 is the vertices set of the path P_1.
2: **Loop:** for each path P_i, (i=2, 3, …, num).
3: Translate the logic expression of the event $E_i=\left(\bigcap_{j=1}^{i-1}\overline{P_j}\right)\cap \boldsymbol{P}_i$ to the union of vertex events based on the Boolean Lemmas [34], namely $E_i=\bigcup_{j=1}^{J_i}\left(\left(\bigcap_{k\in K_j} \boldsymbol{e}_k\right)\cap\left(\bigcap_{s\in S_j}\bar{\boldsymbol{e}}_s\right)\right)$, where $\bar{e}_i$ is the event that that vertex i fails. And K_j and S_j are the set of vertices (i=2, 3, …, num).
4: **Until** all paths P_i, (i=2, 3, …, num) are calculated. (End the loop)
5: Translate the logic expression to the reliability function in Equation (14).
6: **Return** $C(t)$.

eliminating (PIE) algorithm, as given in Table II. According to our definition, the connectivity has the form in

$$C(t)=\sum_{i=1}^{\text{num}} P(E_i)$$
$$=\sum_{i=1}^{\text{num}}\left(\sum_{j=1}^{J_i}\left(\prod_{k\in K_j} R_k(t)\right)\cdot\left(\prod_{s\in S_j}\overline{R}_s(t)\right)\right) \quad (14)$$

where num is the number of paths, $P(E_i)$ is the probability of event E_i that paths 1, 2, …, and i-1 are all unconnected but the path i is connected. J_i is the number of union items in E_i. $R(t)$ denotes vertex reliability, and $R(t)$ = 1-$F(t)$. Here, K_j and S_j are the set of vertices, and for each j they satisfy that $K_j \cap S_j=\emptyset$.

3) *Step* 3: Equation (14) and reliabilities $R_i(t)$ of all vertices at time t, calculate the real-time connectivity.

V. COMPUTATIONAL EXPERIMENT

A. Network Structure

A manufacturing network with 30 vertices is designed for the experiment. This is a directed acyclic network with four source vertices, four sink vertices, and 51 directed edges, whose average in-degree and out-degree are both 1.7. The weight of each directed edge is randomly generated under the condition that each vertex i satisfies $\sum_{j=1}^{n} a_{ij}=1$.

B. Experiment Scheme

To compare the difference in the performance of different vertices after a period of operating, we assume that each vertex has the same initial reliability level and parameters (the Weibull distribution (α, β)), the same probability p of giving wrong judgments about the quality state of low-quality products, and the same distribution of failure-rate increment (the beta distribution (a, b)), where the parameters are $\alpha=2.07\times10^3$, $\beta=2.17$, and $p=0.046$.

Also, we assume that the original material is always high-quality. In other words, inputs of all source vertices are qualified. The feedstocks flowing in each source vertex in unit time are

TABLE III
PARAMETERS OF FAILURE-RATE INCREMENTS

Impact strength	a	b	Mean	Variance
Weak	0.156	8.432×10^5	1.85×10^{-7}	2.194×10^{-13}
Normal	0.156	8.432×10^4	1.85×10^{-6}	2.194×10^{-11}
Strong	1.56	8.432×10^4	1.85×10^{-5}	2.194×10^{-10}

TABLE IV
PARAMETERS OF INITIAL QUALITY-LEVEL

Quality levels	g	$p_{initial}$	Quality levels	g	$p_{initial}$
1σ	31%	69%	3σ	93.3%	6.7%
2σ	69%	31%	6σ	99.99966%	0.00034%

TABLE V
SPARSE METHOD

Algorithm 3: Sparse method for generating event moments of NHPP
Input: Intensity function $\lambda(t)$, current time t, and flow IF during the unit time ($\lambda(t) \le IF$).
Output: The moment t_{next} of next event.
1: **Loop**: Generate next event moment t_{next}; by the homogeneous Poisson process with intensity IF;
2: Accept t_{next} with the probability $\lambda(t_{next})/IF$: Generate a random value r_v during [0,1]; if $r_v \le (\lambda(t_{next})/IF)$, accept t_{next};
3: **Until** a t_{next} is accepted, end the Loop, return the t_{next}.

$IF_1=1.250$, $IF_2=3.750$, $IF_3=3.750$, and $IF_4=1.250$. Then, the flow of each nonsource vertex can be calculated based on the input flows in all source vertices and the weighted adjacency matrix A. Further, we set two variables, the failure-rate increment and the initial quality level of the manufacturing network, to study their impact on system performance. First, in different manufacturing networks, increments of failure rates caused by low-quality feedstocks are heterogeneous, so we give three different Beta distributions to model the strong, normal, and weak impact of low-quality feedstocks on machine failure. As given in Table III, different impact strengths have different means of failure-rate increments, which have ten times difference. Second, we also consider the difference in the initial quality level of the manufacturing network. According to the analysis of the initial percentage of low-quality products in Section III-D, we implement the experiment under four initial quality levels by setting different g parameters and the same $\delta=1\times10^3$, as given in Table IV.

Then, to compute the performance of the manufacturing network, experiments are implemented in MATLAB by the following steps, and the operation time is set as $T=6000$.

1) *Step* 1: Start at $t=0$.
2) *Step* 2: By Algorithm 3 in Table V, generate the moments t_i of next low-quality product in each vertex.
3) *Step* 3: Find the vertex $i*$ that produces the next low-quality product at the earliest moment: $t_i*=\min$ (t1, t2, …, t_{n}).
4) *Step* 4: By random sampling according to the edge weights in (1), find the subsequent vertex $i+$ that receives this earliest low-quality product as its feedstock (flowing time between vertices is not considered).
5) *Step* 5: Generate the failure-rate increment Δr of the vertex $i+$ by the Beta distribution.
6) *Step* 6: Update performance of each vertex until time t_i*: failure rate $r(t)$, failure probability $F(t)$, the number of

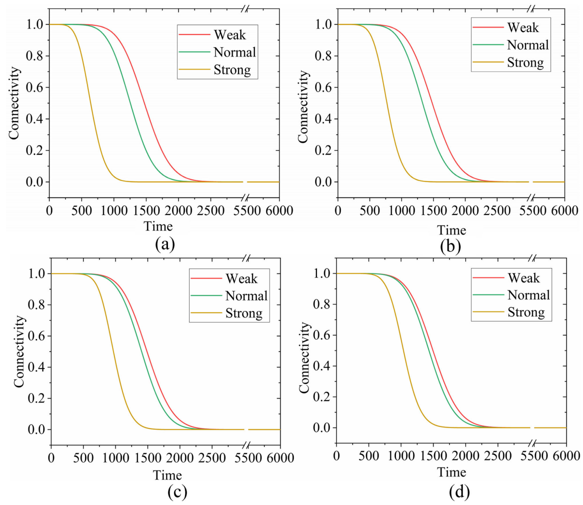

Fig. 5. Connectivity of the manufacturing network. (a) 1σ quality level. (b) 2σ quality level. (c) 3σ quality level. (d) σ quality level.

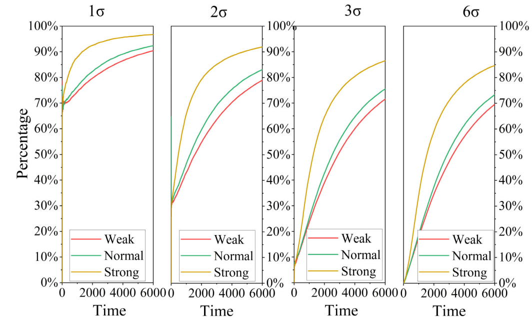

Fig. 6. Accumulative percentage of low-qualified products $P_{\rm cum}$ under different conditions.

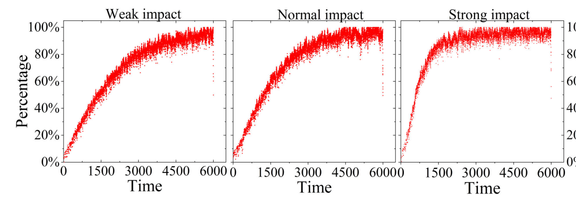

Fig. 7. IPLP $P_{\rm ins}$ under the 3σ condition.

low-quality products $M(t)$, and the number of low-quality feedstocks $N(t)$ (except $i+$, all other vertices do not have the failure-rate increment).

7) *Step* 7: Update the network performance until time t_i*: quality loss Q(t); $P_{\rm cum}(t)$; and connectivity $C(t)$.

8) *Step* 8: If $t_{i^*} < T$, return to step 2; else, end the experiment.

VI. Experimental Results and Discussion

According to the AAP algorithms, we find that the given manufacturing network has 724 paths from source vertices to sink vertices. Then, the connectivity, quality performance, vertex reliabilities, and correlation coefficients between reliability, flows, in-degrees, and quality loss are studied.

A. Connectivity

In this article, we simulate the operation of the given manufacturing network under four initial quality levels and three impact strengths of low-quality feedstocks. As shown in Fig. 5, under any initial quality level, the connectivity of the manufacturing network strongly depends on the impact strength of low-quality feedstocks. Although the means of three impact strengths both have ten times differences (see Table III), the deterioration of connectivity caused by the impact-strength deterioration from normal to strong condition is much faster than the one caused by the impact-strength deterioration from weak to normal condition (in other words, the distance between the green and red lines is much smaller than the one between the orange and green lines). Obviously, the relationship between impact strengths and process-route connectivity is nonlinear. This shows that weakening impact strength of low-quality feedstocks is an effective method to improve the connectivity in a manufacturing network in the earlier stage. However, when the impact strength is weak enough, this method will not be as effective and not be worth further investment.

Moreover, the obtained four figures illustrate that the initial quality level also has strong associations with the connectivity. With the improvement of the initial quality level (from 1 to 6σ), the connectivity will be improved (the three lines move right), especially in the condition of strong impact strength. This proves the impact of low-quality feedstocks on route connectivity in a manufacturing network. Also, when initial quality levels are improved, three lines become more compact, representing that effects of impact strengths are weakened when the initial quality level is improved. Therefore, keeping a high initial quality level also can help the manager to raise the process-route connectivity and reduce the risk of production break in a manufacturing network.

B. Quality Performance

In this part, the two quality indicators in (12) and (13) are analyzed to grasp the quality performance of the manufacturing network. Through the experiment, the initial APLP (at $t = 0$) under different impact strengths are coincident with the experiment assumptions about initial quality levels, as shown in Fig. 6. This proves the validity of the proposed method in modeling the operation of manufacturing networks.

Similar to the connectivity, that the relationship between impact strengths and quality loss of manufacturing networks is also nonlinear. In other words, the APLP deterioration caused by the ten-fold strengthening of impact strength from normal to strong condition is much faster than the one caused by the same scale strengthening from weak to normal condition (the distance between the green and red lines is much smaller than the one between the orange and green lines in Fig. 6). Therefore, reducing the impact strength of low-quality feedstocks can improve the quality performance, but this method could hit a ceiling when the impact strength is weak enough. Also, no matter what impact strength is, a better initial quality level presents a lower APLP at the end time ($t = 6000$). Therefore, considering the interacting behaviors between machines and feedstocks, increasing the initial quality level is also very important for reducing the nonconforming quality in a manufacturing network.

Fig. 7 gives the scatter diagrams of the IPLP $P_{\rm ins}$ in (13) under the 3σ initial quality level, and the time radius is $\Delta t = 10$.

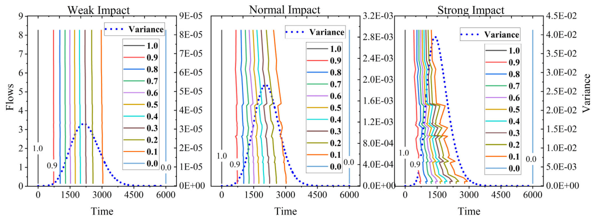

Fig. 8. Contours and variances of vertex reliabilities (the 3σ condition).

With the increase of impact strengths Fig. 7(a) to (c), the IPLP will rise much faster during the growth stage. This represents that low-quality feedstock with a strong impact will worsen the manufacturing quality more quickly. Also, Fig. 7 shows that the deterioration of manufacturing quality is not only represented on the increase of IPLP, but also their instabilities. No matter what impact strengths of low-quality feedstocks are, the high IPLP is always accompanied by a wider range of values, representing the higher instability of manufacturing quality.

C. Vertex Reliabilities

In this section, we will analyze vertex reliabilities when subject to the shock of low-quality feedstocks, namely $R_i(t) =$ 1-$F_i(t)$, where $F_i(t)$ is the failure probability of each vertex i in (4). In the experiment, we assume that all machines have the same initial reliability—the same Weibull distribution, so that the deviation of vertex reliabilities can reflect the impact of low-quality feedstocks on different vertices. In other words, lower reliability means more impact from low-quality feedstocks. We define the variance of vertex reliabilities at different times by

$$V(t) = \frac{1}{n'} \sum_{i=1}^{n'} (R_i(t) - \mu_{Ri})^2 \tag{15}$$

where n' is the number of vertices subject to the impact of low-quality feedstocks. In this article, except the source vertices (assume that original materials are always high-quality in this experiment), all other vertices will suffer the impact of low-quality feedstocks. μ_{Ri} is the mean reliability of all interested vertices at time t.

Fig. 8 gives the variances of vertex reliabilities in the time axis and the contour lines of vertex reliabilities on the time-flow plane, both of which are analyzed for different impact strengths under the 3σ initial quality level. As we can see, under the weak impact of low-quality feedstocks, the contour lines are very symmetrical, and the variance of vertex reliabilities is much small. However, with the increase of impact strengths of low-quality feedstocks, the contour lines become more and more unsymmetrical, where the contour lines become more compact at high flows, meaning a faster deterioration of vertex reliability. Also, the variance of vertex reliabilities under the strong impact is much greater than the ones under the weak and normal impacts. These characters show that machine reliability has strong relevance to the impact strength of low-quality feedstocks and flows of products. Furthermore, corresponding changes about variance and contour lines also illustrate that the sensitivity of machine reliability to flow (or production speed) greatly depends on the impact strength of low-quality feedstocks.

Combining this contour analysis and the connectivity analysis in Section VI-A, we conclude that vertex with high flow volume is the key reason causing the quick descent of connectivity under the strong impact. This is because the reliability of vertices with high flow volume will descend faster, as the most compact contour lines shown in Fig. 8. This tells us that, to avoid the production break in a manufacturing network, the vertex with high flow volume requires more attention, especially when the impact strength of low-quality feedstocks is high.

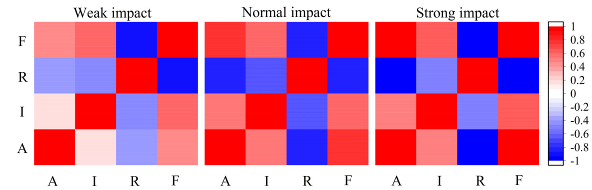

Fig. 9. Correlation chart (the 3σ condition) (A: APLP; I: In-degree; R: Reliability; F: Flows.).

D. Correlation Analysis

In this section, we analyze the sample Pearson correlation coefficient between four variables of all intermediate vertices by the (16) [35]: reliability; flows; in-degrees; and percentages of low-quality products

$$\rho_{XY}(t) = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{x_i(t) - \mu_X(t)}{\sigma_X(t)} \right) \left(\frac{y_i(t) - \mu_Y(t)}{\sigma_Y(t)} \right) \tag{16}$$

where $X(t) = \{x_1(t), x_2(t), \ldots, x_N(t)\}$ and $Y(t) = \{y_1(t), y_2(t), \ldots, y_N(t)\}$ are the compared variables, referring to the set of low-quality product percentages, reliabilities, flows, or in-degrees of all intermediate vertices at time t. N is the number of intermediate vertices. $\mu_X(t)$ ($\mu_Y(t)$) and $\sigma_X(t)$ ($\sigma_Y(t)$) are the mean and standard deviation of $X(t)$ ($Y(t)$). Then, we use the average Pearson correlation coefficients at different times as the measure of correlations between variables $X(t)$ and $Y(t)$, as shown in

$$Coc_{XY} = \frac{1}{Z} \sum_{i=1}^{Z} \rho_{XY}(t_i) \tag{17}$$

where Z is the frequency of measurements, and $\rho_{XY}(t_i)$ is the measured correlation coefficient at time t_i. Also, we know that the reliability curve of machines has a similar shape shown in Fig. 5, whose values are stable at 1 or 0 at the beginning and end, representing two extreme situations of machine conditions. To avoid these extreme data, our correlation analysis samples compared variables in a period from the instant that the network connectivity reaches 0.9 to the instant that it reaches 0.1.

In Fig. 9, we use the APLP [In (12)] as the quality-related variable to evaluate the correlation coefficients. It shows that vertex reliability has negative correlations with the other three variables. Specifically, reliability and flows always have strong negative correlations, then reliability and in-degree always have weak negative correlations, but reliability and the APLP show gradually strengthening negative correlations when the impact strength of low-quality feedstocks increases. These characters further verify the conclusion in Section VI-C that vertex reliabilities can be impacted by the flow and impact strength of low-quality feedstocks in a manufacturing network. Also, we can conclude that the flow is a dominant indicator for estimating the risk of machine breakdown in a manufacturing network

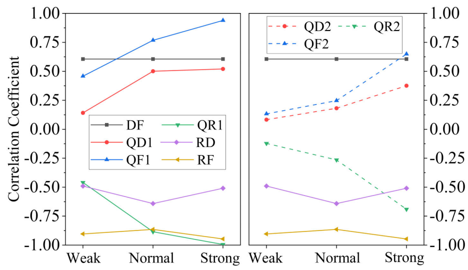

Fig. 10. Correlation coefficients (the 3σ condition) (DF: in-degree and flows; RD: reliability and in-degree; RF: reliability and flows; QD1: APLP and in-degree; QF1: APLP and flows; QR1: APLP and reliability; QD2: IPLP and in-degree; QF2: IPLP and flows; QR2: IPLP and reliability).

with machine and feedstocks interdependence. Therefore, the vertex with high-flow volumes requires more attention during the operation, e.g., giving more preventive maintenance.

Additionally, the APLP of vertices always has positive correlations with its in-degree and flows, which are strengthened when the impact strength of low-quality feedstocks increases. Obviously, the correlations between APLP and the other three variables greatly depend on the impact strength of low-quality feedstocks. Here, the positive correlation between APLP and flows is in line with Gardner's [36] idea in the research on balancing priorities of production speed and conformance quality. Therefore, balancing the flow in a manufacturing network to average the load in each machine is also one effective method to reducing the risk of production break and quality loss. Finally, we learn that vertex flows have a medium positive correlation with its in-degree, representing that network structure can also impact its reliability and quality performance by impacting the flows.

Next, we also analyzed the correlations when replacing the APLP by the IPLP, where $\Delta t = 10$. The comparisons are illustrated in Fig. 10. Although they have the same trends, the correlations between IPLP and three other variables (QD2, QF2, and QR2) are much weaker than the APLP (QD1, QF1, and QR1). This illustrates that the cumulative effect is a very important reason for the phenomenon that interacting behaviors can greatly reduce the performance of manufacturing networks. This reminds us of the importance of process control in the operation of manufacturing networks. Process control, such as preventive maintenance of machines and inspection of work-in-process, can greatly prevent the deterioration of machine reliability or propagation of low-quality feedstocks, thereby reducing the interacting behaviors between them.

VII. Conclusion

In this article, a generalized framework was established for interdependence modeling of machine reliability and feedstock quality in manufacturing networks, and a performance analysis algorithm of route connectivity and quality loss was proposed. Prior researches have shown that many dynamic interacting behaviors exist in manufacturing systems, but very little was done to analyze the impact of these phenomena on manufacturing networks. Therefore, this article focuses on the interdependence between machines and feedstocks, develops the models of machine reliability and processing quality in the presence of heterogeneous feedstocks, and investigates the algorithm for computing the performance of irregular manufacturing networks. The new modeling framework sheds insights into the dynamic interacting behaviors caused by heterogeneous feedstocks in a manufacturing network.

The present article focuses mainly on modeling machine-feedstock interdependence and evaluating system performance in a manufacturing network, but many new problems in manufacturing networks still need to be studied further. For example, since the machine may suffer different operational conditions during different periods, a multiperiod model is necessary to grasp the dynamic operating environment. Also, as we concluded, feedstock flow can greatly affect the performance of manufacturing networks, but how to control the flow to balance the task requirement and performance loss still needs further study. Therefore, this article will inspire some new exploration of these issues that could be interests of future research.

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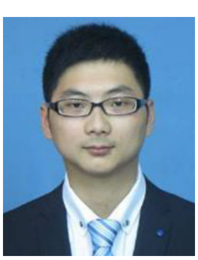
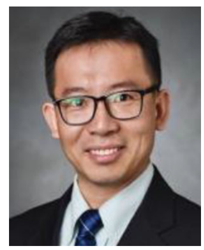


Zhenggeng Ye (Student Member, IEEE) received the B.S. degree from the Henan University of Science and Technology, Luoyang, China, in 2012, and the M.S. degree from Jilin University, Changchun, China, in 2015, both in mechanical engineering. He is currently working toward the Ph.D. degree in management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

From November 2019 to October 2021, he is currently a Visiting Scholar with Complex Systems Monitoring, Modeling and Control Laboratory in the Harold and Inge Marcus Department of Industrial and Manufacturing Engineering, Pennsylvania State University, University Park, PA, USA. His research interests include manufacturing system modeling, analysis, and optimization.

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.



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 a Professor with the Harold and Inge Marcus Department of Industrial and Manufacturing Engineering, The Pennsylvania State University, University Park, PA, USA. Prior to joining Penn State in 2015, he was an Assistant Professor with the Department of Industrial and Management Systems Engineering, University of South Florida, from 2009 to 2015. 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 is a recipient of 2015 Outstanding Faculty Award at the University of South Florida.

Zhiqiang Cai (Member, IEEE) received the B.S. degree in aircraft design and engineering, the M.S. degree in management science and engineering, and the Ph.D. degree 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.

Fuli Zhou received B.Sc. degree in industrial engineering from the Henan University of Science and Technology, Luoyang, China, in 2012, and the M.Sc. and Ph.D. degrees in management science and engineering from Chongqing University, Chongqing, China, in 2014 and 2018, respectively.

He is currently a Visiting Scholar with the NUS Business School, Singapore, and is currently a Lecturer with the School of Economics and Management, Zhengzhou University of Light Industry, Zhengzhou, China. His research interests include quality management and industrial engineering.