Degradation Analysis of Machine Processing Accuracy for Manufacturing Systems with Effect of Unqualified Products

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Key Words: processing accuracy, dynamic degradation, product quality, failure propagation, non-homogeneous Poisson process, log-normal distribution.

SUMMARY & CONCLUSIONS

The machine fault prognosis method by monitoring the manufacturing system dynamical performance has been widely studied recently, which is also the most common and significant problem faced in manufacturing industries. In a manufacturing system, machine is the key component. The dynamic and precise identification of the healthy state of the machine can support the decision making of production operation. In this paper, since the propagation of unqualified products will lead to the deterioration of machine's processing accuracy, quality of imported products is considered to be an important factor affecting machine's performance. Considering this practical scenario, a non-homogeneous Poisson process is applied to model the number of quality failures in a manufacturing system, and the log-normal distribution is used to depict the impact strength of unqualified products to a machine. At last, the applicability of the proposed model is discussed for the serial manufacturing system, and an analysis procedure of machine's accuracy degradation is provided to illustrate its actionability.

1 INTRODUCTION

Product quality greatly depends on the processing accuracy of machines in manufacturing systems. With the development of new products, the requirement of high processing accuracy for machines is much more urgent. As an important factor of production scheduling and maintenance decision, the degradation analysis of machine processing accuracy contributes to the resources deployment and optimization of the manufacturing system.

In traditional evaluation of machine processing accuracy, several factors have been taken into consideration, such as geometric errors, thermal errors, and tool wear [1-3]. In other studies, static or dynamic factors are considered to be the main factors causing dimensional deviations, such as component weight, guide imperfection, cutting forces, motion, and acceleration [4]. Considering the interaction between the variation process of machine tools accuracy and parts cutting process, an identification method is proposed to prioritize the importance of key accuracy characteristics of machine tools for parts machinability [5]. In addition, machine learning is also used in degradation analysis of machine processing accuracy evaluation. The run-to-failure bearing data is used to train the prediction model of degradation by relevance vector machine (RVM) technique and logistic regression (LR), and the failure probability of individual machine component is estimated [6].

Even these researches have considered machine's working conditions thoroughly, it is still difficult to analyze the degradation of machine processing accuracy from the viewpoint of whole manufacturing process. In industrial plants, machine processing accuracy is influenced by multiple factors, including the working conditions of machines and characteristics of manufacturing objects. In other words, machine processing accuracy is affected by internal factors inside the machine and external factors from sources outside the machine, all of which may cause the degradation of machine processing accuracy.

Moreover, time-varying and dynamic behaviors are also typical features of manufacturing systems. These dynamic behaviors, regarding as significant attributes of engineering systems, may lead to unstable states of systems [7, 8]. To analyze engineering systems with time-varying degradation rates, inverse Gaussian process models were proposed by considering constant, monotonic, and S-shaped degradation rates [9]. Considering the wear's influence on accuracy degradation, an extended wear model was proposed on the basis of Archard wear theory, which assisted to establish the accuracy degradation model under time-varying motion and loading working conditions [10]. Obviously, time-varying feature has been widely taken into account in various engineering systems, which should also be considered in a manufacturing system. So, the dynamically random effects will be also incorporated into the degradation process models in this paper.

In general, machines' performance will evolve over time when they interact with each other and with the environments in a manufacturing system. The unqualified product, which is engendered by upstream machines with poor manufacturing accuracy, is one kind of external factors in manufacturing systems [11]. When processing in downstream machines, they

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will aggravate the degeneration of the machine manufacturing accuracy. Obviously, unqualified products are carriers of quality failure in manufacturing systems, leading to the dependency among the degradation of manufacturing accuracy in different machines. This phenomenon will increase the difficulty of tracking mutable manufacturing accuracy, which has become the key problem of product quality control in traditional and next-generation innovation practices. Hence, there is a great urgency to harness and exploit the degradation of machine manufacturing accuracy under such dynamic and interactive behaviors.

In this paper, we analyze the dynamic and interactive behaviors between machines under the impact of unqualified products in manufacturing systems. Based on the dependency among dynamic interactive behaviors, non-homogeneous Poisson process models and the log-normal distribution are introduced to describe the degradation process of machine processing accuracy. In addition, the applicability of proposed model is also discussed, and specific evaluation procedure is illustrated.

2 SYSTEM DESCRIPTIONS

In a manufacturing system, machines, products and inspection processes are three key factors affecting system's performance [12, 13]. In practice, the processing accuracy reliability is defined as the ability to perform machine's specified processing accuracy under the stated conditions during a given period of time, which will also play an important role on the quality of products [11]. For a single machine, processing accuracy will be affected by multiple factors, such as tool wear and imported unqualified products (works in process). Generally, tool wear can be regarded as the internal sources, which will cause the stable continuous degradation of machining accuracy. But as external sources, imported unqualified products will append noise to machine's degradation and cause the interaction between serial machines, as shown in Figure 1. Due to the degradation of processing accuracy, unqualified products will be produced by upstream machine 1 and imported into the downstream machine 2 when the inspection process fails. Obviously, the propagation of unqualified products will occur among serial machines. So, the manufacturing systems with serial machines will be addressed in this paper.

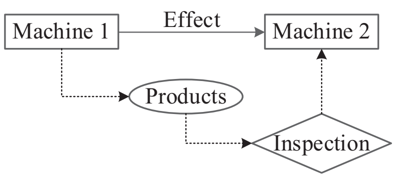

Fig 1. Interactions between machines

Before modeling the manufacturing system, some assumptions are given as follows.

(1) Discrete-part manufacturing processes are considered, where the number of processed products is treated as the time index;

(2) If there is no inspection process after a machine, all products can be considered to pass the test, which means the inspection process is virtual;

(3) The propagation of unqualified products is considered to be instantaneous, namely the transporting time is not considered in this paper;

(4) The impact strengths of propagated quality failures produced by the same machine are independent and identical distributed;

(5) The number of quality failures and their impact strengths are independent random variables.

3 MODELING OF MANUFACTURING SYSTEM

3.1 Quality Failure Model

Quality of products is affected by machine's processing accuracy. With the degradation of machine's accuracy, the occurrence of unqualified products will be more frequent. Therefore, we need a stochastic process owing a time-varying probability that events may be more likely to occur at certain times than at other times. In this paper, the non-homogeneous Poisson process (NHPP) is used to depict the number $M(t)$ that unqualified products occur. And the $\{M(t),\ t\geq 0\}$ has the following properties, as

(1) $M(0)=0$;

(2) The process has independent increments;

(3) $P\{M(t+h)-M(t)\geq 2\}=o(h)$;

(4) $P\{M(t+h)-M(t)=1\}=\lambda(t)h+o(h)$,

where $\lambda(t)$ is the intensity function. Obviously, the intensity function $\lambda(t)$ is proportional to the degradation of machine's processing accuracy. With the aggravation of machine's accuracy degradation, the probability that unqualified products occur during working will increase.

Assume that

$$m(t)=\int_0^t \lambda(s)ds\,. \tag{1}$$

Then, we have the probability function of NHPP as

$$\begin{aligned} & P\{M(t+s)-M(s)=n_m\} \\ & = e^{\{-(m(t+s)-m(t))\}} \frac{\left[m(t+s)-m(t)\right]^{n_m}}{n_m\,!}\,, \end{aligned} \tag{2}$$

where $n_m \geq 0$. Namely, $M(t+s)$-$M(t)$ follows the Poisson distribution with mean $m(t+s)$-$m(t)$ [12].

In a manufacturing system, the inspection process can effectively prevent unqualified products propagating to downstream stations and reduce machine's degradation caused by random shocks from unqualified products [11]. But inspection process does not always work successfully. Then unqualified products will be propagated to downstream stations, and we call this phenomenon as the quality failure. Obviously, for each unqualified product, the inspection process has only two results. We assume that random variable Y is the result of inspection process, which obeys the Bernoulli distribution, as

$$\begin{cases} P\{Y=1\} & = p \\ P\{Y=0\} & = 1-p \end{cases}. \tag{3}$$

Here, Y=1 represents that inspection process has a wrong judgement for the unqualified product. Then, we can depict the number of propagated and not propagated quality failures by two different stochastic variables $\{N(t+s)-N(s), t\geq 0, s\geq 0\}$ and $\{N'(t+s)-N'(s), t\geq 0, s\geq 0\}$, as shown in Equations (4) and (5).

$$N(t+s)-N(s)=\sum_{i=1}^{M(t+s)-M(s)} Y_i , \tag{4}$$

$$N^{'}(t+s)-N^{'}(s)=\sum_{i=1}^{M(t+s)-M(s)} (1-Y_i) . \tag{5}$$

If we assume that there will be n ($n\leq n_m$) quality failures propagated into downstream machines during t and (n_m-n) quality failure will be discovered and not propagated, we can obtain Function (6).

$$\begin{aligned} & P\{N(t+s)-N(s)=n, N^{'}(t+s)-N^{'}(s)=n_m-n\} \\ & = P\{N(t+s)-N(s)=n, N^{'}(t+s)-N^{'}(s)=n_m-n \mid M(t+s)-M(s)=n_m\}\cdot P\{M(t+s)-M(s)=n_m\} \\ & = C_{n_m}^{n} p^n (1-p)^{n_m-n} \cdot e^{\{-(m(t+s)-m(t))\}} \frac{[m(t+s)-m(t)]^{n_m}}{n_m!} \\ & = \frac{n_m!}{n!(n_m-n)!} p^n (1-p)^{n_m-n} \cdot e^{\{-(m(t+s)-m(t))\}} \frac{[m(t+s)-m(t)]^{n_m}}{n_m!} \\ & = e^{\{-p\cdot(m(t+s)-m(t))\}} \frac{[p\cdot(m(t+s)-m(t))]^n}{n!} \cdot e^{\{-(1-p)\cdot(m(t+s)-m(t))\}} \frac{[(1-p)\cdot(m(t+s)-m(t))]^{n_m-n}}{(n_m-n)!} \end{aligned} . \tag{6}$$

Obviously, $N(t+s)$-$N(s)$ and $N'(t+s)$-$N'(s)$ can be considered as two independent variables which obey NHPP with $p(m(t+s)-m(t))$ and $(1-p)(m(t+s)-m(t))$ as the mean values respectively [14].

$$\begin{aligned} & P\{N(t+s)-N(s)=n\} \\ & = e^{\{-p\cdot(m(t+s)-m(t))\}} \frac{[p\cdot(m(t+s)-m(t))]^n}{n!} . \end{aligned} \tag{7}$$

3.2 Degradation Model for Processing Accuracy

As a mechanical system, machine's processing accuracy is considered to be affected by several factors, such as components' wear, noise and other random factors. According to the research of Archard and Dawson, machine's degradation closely depended on the load force, sliding distance, and the contacting surface, which would be changed by the dimensional deviations of unqualified products [15]. Comparing with the degradation under the stable working condition, the volatile working condition may have a significate different degradation process due to dealing with unqualified products.

When shocks of unqualified products occur, their impacts will also be different due to the diverse deviations of the products. Therefore, we assume the impact strength from propagated quality failure to machine's processing accuracy is a random variable S. It is clear that variable S has following properties:

(1) S must take non-negative values;

(2) Because dimensional deviation of unqualified products is a continuous variable, its impact strength S will also be a continuous random variable;

(3) Impact strength S_i of different propagated quality failures are independent and identical distributed;

(4) Usually, dimensional deviation of unqualified products Q can be considered to obey a normal distribution. In addition, impact strength S of propagated quality failure can be regarded as the function of Q, namely $S=f(Q)$.

Therefore, we will use the log-normal distribution to depict the impact strength S of propagated quality failures in this paper, which satisfies above properties, namely $S=e^Q$. If dimensional deviation of unqualified products Q obeys a normal distribution $N(\mu,\sigma^2)$, we can obtain the density function as

$$\begin{aligned} g(s) = \frac{1}{\sqrt{2\pi}\sigma s}\exp\{-\frac{1}{2\sigma^2}(\ln s-\mu)^2\} \\ s>0, \sigma>0, -\infty<\mu<\infty \end{aligned} . \tag{8}$$

In this paper, it is assumed that machine's processing accuracy will be reliable if it does not exceed the threshold H. The probability density function of machine's accuracy failure is depicted by $f(t;\alpha,\beta)$, and its distribution function and reliability function respectively are $F(t;\alpha,\beta)$ and $R(t;\alpha,\beta)$, where $R(t;\alpha,\beta)=1-F(t;\alpha,\beta)$. Obviously, the failure rate can be obtained by

$$r(t;\alpha,\beta)=\frac{f(t;\alpha,\beta)}{\overline{F}(t;\alpha,\beta)}=\frac{f(t;\alpha,\beta)}{R(t;\alpha,\beta)} , \tag{9}$$

where variables α and β are shape and scale parameters respectively. This function depicts the original degradation process of machine's accuracy, which is not affected by shocks of propagated quality failures. For any time series $t_1,t_2,\ldots,t_i,t_{i+1},\ldots$, we assume that during the work period $\Delta t_i=t_{i+1}-t_i$, there are $N(\Delta t_i)$ propagated quality failures with impact strength $S_j(j=1,2,\ldots,N(\Delta t_i))$. Under the impact of propagated quality failures, assume that machine' processing accuracy has a new failure rate $r(t;\alpha',\beta')$ with following new shape and scale parameters, as

$$\begin{cases} \alpha' = f_1(\alpha, \sum_{j=1}^{N(\Delta t_i)} S_j) \\ \beta' = f_2(\beta, \sum_{j=1}^{N(\Delta t_i)} S_j) \end{cases}, \tag{10}$$

where $t \in [t_i, t_{i+1})$. If $\sum_{j=1}^{N(\Delta t_i)} S_j = 0$, there are $\alpha' = f_1(\alpha,0) = \alpha$ and $\beta' = f_2(\beta,0) = \beta$.

We can find that machine's processing accuracy will deteriorate with a worse failure rate during the shocks of propagated quality failures. But how will the failure rate change after these shocks? Therefore, another important problem about failure rate's recovery after the shock of propagated quality failure should be discussed. In this paper, we consider that machine's processing accuracy will have two completely different changes after the shock. One is that the failure rate will return to the state before shocks, which can be defined as the resilient failure rate. So, for the next work period $t \in [t_{i+1}, t_{i+2}]$ without shocks of propagated quality failures, the failure rate will return to $r(t;\alpha,\beta)$. Another one is that the failure rate will maintain the state during shocks, which can be defined as the vulnerable failure rate. And for the next work period $t \in [t_{i+1}, t_{i+2}]$ without shocks of propagated quality failures, the failure rate will also be $r'(t;\alpha',\beta')$.

4 MODEL APPLICATION DISCUSSION

4.1 Applicability Analysis for A Serial Manufacturing System

In a manufacturing system, failure's propagation usually occurs among machines connected in a serial structure. The serial manufacturing system is a typical system structure in industry which has failure's propagation, as shown in Figure 2. Supposing that a serial manufacturing system has n machines and inspection processes, the failure propagation will have two stages. Firstly, degradation of machine processing accuracy will affect products' quality by influencing their dimensional deviations, which will be represented on the number of propagated quality failures $N(t+s)-N(s)$ after the inspection process. Secondly, failure propagation occurs between machines, where propagated quality failures will play an important role in the degradation of downstream machine's processing accuracy. In a serial manufacturing system, all propagated quality failures will be transported into the downstream machine. In addition, before analyzing machine's degradation under the effect of unqualified products, the parameters illustrated in Table 1 should be obtained.

On the basis of known parameters, three steps will be implemented to finish the degradation analysis, as shown in Figure 3. The detailed illustrations are shown as follow.

Step 1: Analyze propagated quality failures from the upstream machine. There will be two operations being accomplished in this step.

- Operation 1: Identify the number of propagated unqualified products from upstream machine during $[s,t+s]$.
- Operation 2: Estimate the impact strengths of each propagated unqualified products by the Log-normal distribution in Function (8).

Step 2: Evaluate the degradation of machine processing accuracy. There will be also two operations in this step.

- Operation 1: On the basis of the probability density function $f(t;\alpha,\beta)$, the new shape and scale parameters α', β' are estimated by the Function (10).
- Operation 2: Calculate machine's novel probability density function $f'(t)$ and failure rate $r'(t)$ during $[s,t+s]$.

Step 3: Analyze the propagation of quality failures into the next machine. Two operations are given here.

- Operation 1: Evaluate the number of unqualified products produced in this machine by the non-homogeneous Poisson process in Function (2).
- Operation 2: Estimate the number of propagated unqualified products into the next machine by the non-homogeneous Poisson process in Function (7)

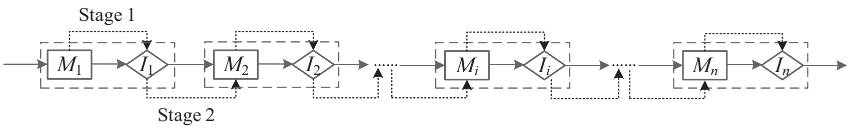

Fig 2. Failure's deterministic propagation in a serial manufacturing system

Table 1- Known Parameters in The Proposed Model

No.	Parameters	Symbols
1	Intensity function of NHPP depicting unqualified products' occurrence.	$\lambda(t)$
2	The probability that inspection process has a wrong judgement for the unqualified products.	p
3	The normal distribution that the dimensional deviation of unqualified products Q obeys.	$N(\mu,\sigma^2)$
4	The original probability density function of machine's accuracy failure.	$f(t;\alpha,\beta)$
5	Functions of shape and scale parameters under the influence of propagated unqualified products.	f_1, f_2

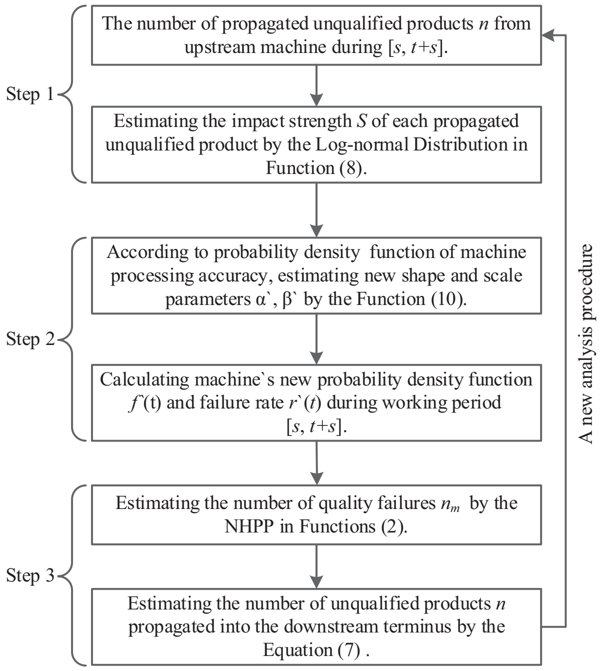

Fig 3. Procedure of the degradation analysis

4.2 Discussions

According to above-mentioned steps and known parameters, machine's dynamic degradation process under the effect of unqualified products can be evaluated effectively. Among the listed known parameters in Table 1, the intensity function $\lambda(t)$, the probability p and the normal distribution $N(\mu,\sigma^2)$ can be easily obtained according to the statistical analysis and parameter estimation methods. In addition, the original probability density function of machine's accuracy failure, $f(t;\alpha,\beta)$, can also be obtained based on the reliability evaluation of machine when it operates without processing parts. The major difficulty is how to estimate the functions of shape and scale parameters under the influence of propagated unqualified products, f_1 and f_2.

In practical evaluation processes, the regression analysis is an effective method to estimate the functional relationship between variables. By dividing the time into several intervals, we can obtain degradation values during each interval by partition statistics method. In addition, because the probability density functions in different intervals follow the same distribution type with different parameters, the new shape and scale parameters, α', β', can be obtained by the parameter estimation method. Further, the functional relationships, f_1 and f_2, can be obtained by the regression analysis utilizing the original and new shape and scale parameters.

In practical application, the evaluation cycle can be set according to the batch, and product's need for the accuracy is considered to be the threshold of processing accuracy. Then, machine's degradation can be monitored and predicted by its operation data during the evaluation cycle. Eventually, the machine approaching the accuracy threshold will be identified in advance and recommended to the maintenance plan. Therefore, the proposed method can be considered to own a well performability. Simultaneously, the proposed model has a wide range of applicability for different manufacturing systems, such as the system consisted of machines with resilient or vulnerable failure rate.

5 CONCLUSION AND FUTURE WORK

This paper proposed a new degradation analysis method for machine processing accuracy, which considered the effect of unqualified products. In this model, the NHPP is used to depict the number of unqualified products produced by a machine, and the number of propagated unqualified products after the inspection process is also derived to satisfy a NHPP. Using the Log-normal distribution with time-varying parameters, the dynamic impact of unqualified products to machine's degradation is evaluated. Then, the feasibility of the proposed models is discussed, and the evaluation procedures are illustrated in detail. Simultaneously, the serial manufacturing system with propagations of unqualified products is taken into account during the modeling process. According to the discussions, the proposed model can help us effectively accomplish the goal of analyzing the degradation of machine processing accuracy in a dynamic environment caused by the propagated unqualified products.

In future, both technology and application need to be consummated. At the technical level, this paper developed an analysis frame with reasonable mathematical models, but specific implementations still need to be further enriched. In industrial applications, some numerical examples or simulation studies need to be developed to illustrate the application of this approach. Then, some more specific and detailed analysis about manufacturing systems with different properties will be finished based on this general model.

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