## Comprehensive Complexity-Based Failure Modeling for Maintainability and Serviceability

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#### Abstract:

Failures are the primary triggers for repair and maintenance actions. A clear definition of failure events is important in order to improve maintainability and serviceability. A comprehensive complexity-based mathematical definition of failure is introduced. The applicability of the developed failure model to different complexity definitions is discussed. A new metric is introduced to capture the change in complexity associated with function degradation. A case study is presented to illustrate the application of the new failure definition and metric. The developed approach for failure modeling can be used for maintenance planning.

## Keywords:

Failure, Maintenance, Serviceability, Complexity, Manufacturing Systems

#### 1. INTRODUCTION:

## 1.1. Problem statement

Current research in failure-induced maintenance investigated two main issues:

- 1) Many maintenance activities in manufacturing systems are triggered by machine's failure. This failure is normally interpreted as physical failure that is easily identified. But, in many cases, the machine fails to perform its intended function, such as maintaining a certain dimensional tolerance, without a noticeable physical failure. This type of functional failure is not precisely defined in literature. However, it may cause significant production losses and lead to increased operational complexity.
- 2) Machines have two main modes of failure, sudden and gradual. In the sudden failure mode, a machine switches from an operating state directly to the failure state. But in the gradual mode, the machine experiences many in-between states before reaching failure. Nevertheless, most of the reliability and maintenance related research in manufacturing systems use a failure rate model based on the two states assumption. This assumption neglects the nature of the actual machine failure, which leads to ineffective maintenance strategies.

# 1.2. Literature survey

The term "failure" is widely used in daily life and in the branch of reliability and maintainability engineering. From a manufacturing perspective, machine failure is the trigger for corrective maintenance. Therefore, it is important to detect failures as, or even before, they occur. Thus, modern manufacturing systems need reliable failure detection mechanisms. This fact has been emphasized by including the diagnosis ability as one of the key characteristics of new types of manufacturing systems such as flexible or reconfigurable manufacturing systems

[1]. The effect of the used failure detection mechanism on the manufacturing system performance depends on the adopted failure definition [2]: "A common element that is vastly ignored but is rather critical to a sound reliability specification is the definition of equipment failure. Even the most vigorous reliability testing program is of little use if the equipment being tested has poorly defined failure parameters".

There are physical and operational approaches for failure definition found in both academic literature and industrial practice. The physical approach in defining machine failure has been widely accepted where failure is defined as "an undesirable and unplanned change in an object, machine attribute or the machine structure" [3]. Therefore, failure is synonymous with breakdown [4]. The breakdown is characterized by a physical change in any of the machine modules or machine parameters such that the machine is totally unable to continue performing its function. A breakdown of any of the machine tool modules (heads, controls, etc.) is an example of this failure type.

The second approach in defining failure is based on the machine operation. Fashandi and Umberg [2] defined failure as: "Any unplanned interruption or variance from the specifications of equipment operation". An example of the application of this failure definition is used in the quality control charts where it is indicated that a machine is in need for repair if the process carried out by that machine is out of control [5]. Some researches consider operational failure as a symptom of physical failure such as Umeda et al. [3], who defined a failure symptom as the function that has not been performed due to a failure.

Physical failures normally lead to operational failures; however, the reverse is not necessarily true. A machine operational failure can happen without being preceded by physical failure. For example, a cutting tool breakage (physical failure) would certainly lead to machine functional failure, while deterioration of machining precision to a level below specifications (operational failure) can happen without any physical failure in the machine or the tool. This concept of functionality versus physical state has been considered by Umeda et al. [6]. They developed a new concept of maintenance where

maintaining the system functionality is emphasized instead of its physical state. Based on this concept, Umeda et. al. [7, 8] developed the Self-Maintenance Machine (SMM) that keeps performing its basic functions even during periods of physical failure. It is clear from this discussion that functional failure of any module is the triggering event for either functional delegation or control action. Nevertheless, a precise definition of the functional failure is still needed.

The previous review shows that there is no unified and precise definition of physical and operational failure in the manufacturing. This ambiguity about failure may lead to ineffective fault detection and hence loss of production capacity.

### 2- FAILURE DEFINITION

Grall *et al.* [9] assumed that the deterioration condition of any device can be modeled by a stochastic ageing process such that when the system is new, the ageing variable equals zero and when the ageing variable reaches a predetermined level, called failure level (*L*), the system is deemed to have failed. This model is shown in Figure (1).

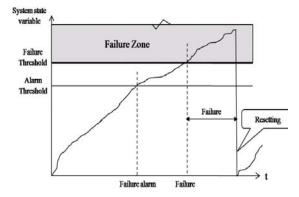


Figure 1 Failure Threshold Definition

The curve in Figure (1) represents the system states at different time instances and shows that the system state variable increases with time till it reaches the failure threshold (L). This model precisely defines the failure by a threshold level of a system state variable beyond which, the system is considered failed even if it is still working. However, Grall et al. [9] did not specify the system state variable on which the failure threshold should be based. Hence, their model is not considered complete. From the literature survey, it can be concluded that both types of failures, physical and functional, lead to the same result; loss of system functionality. Therefore, the system functionality is a suitable system state variable for defining failure.

The concept of system functionality is modeled in the Axiomatic Design and Complexity theory introduced by Suh [10]. The design world is assumed to consist of four domains; customer, functional, physical and process domains such that the design process is an interplay between those domains where the design is described in each domain by certain parameters. They are respectively customer wants, functional requirements, design parameters, and process parameters whereas system functionality is described by the Function Requirements (FRs). Suh [11] defined the information content of the system as:

$$I_{sys} = -\sum_{i=1}^{m} \log_2 P_i \tag{1}$$

Where :  $I_{sys}$  information content of the system  $P_i \qquad \text{probability that FR}_i \text{ is satisfied}$   $m \qquad \text{number of FRs}$ 

The information content is a direct measure of the uncertainty of satisfying the function requirements. This uncertainty is therefore a measure of the system complexity [12]. Complexity is expressed mathematically by the following equation:

Complexity 
$$C_R = \log_2 1/P_F - \log_2 \int_{\text{design Range}} f(FR)dFR$$
(2)

Accordingly, as complexity increases the uncertainty of satisfying the functional requirements also increases. Thus, complexity is a measure of system functionality. Therefore, it is proposed to use the complexity as the machine state variable in the failure model. Consequently, the definition of functional failure can be stated as: "The manufacturing system fails to perform its intended function(s) when its Complexity reaches a predetermined threshold level F". The determination of the failure threshold level F is a strategic management decision where many factors are to be traded off including cost, product quality, and system availability. This definition is shown in Figure (2), which shows the Complexity change for a typical machine tool as it increases with time.

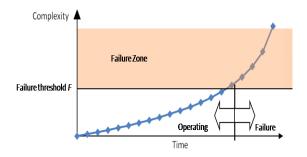


Figure 2 Functional failure definition

According to the proposed definition, the machine is considered good for production as long as the Complexity is less than the failure threshold, and as the complexity exceeds the failure threshold (the shaded region), the machine is deemed to have failed.

The application of the proposed failure definition can be explained using the example presented by ElMaraghy et al. [13]. Assume that the functional requirement of a machine is to satisfy a specified production demand. This determines the design range to lie between the two extremes of the expected demand. When the machine is new, the machine availability distribution lies completely within the functional design range, hence, the demand would certainly be satisfied and the complexity would be zero. As the machine ages, the failure rate increases and the availability distribution shifts away from the design range and the certainty of fulfilling the demand decreases. Hence, the complexity increases. Assuming the minimum acceptable demand satisfaction certainty is 90%, the Failure threshold =  $-\log_2 0.9 = 0.152$ . Therefore, when the availability Complexity reaches 0.152, the machine is considered functionally failed.

Although the developed failure model relies on an uncertainty-based Complexity measure, the model can also be applied to other Complexity definitions. For example, ElMaraghy and Urbanic [14] derived a relationship for process Complexity factor as a function of physical and cognitive efforts of the process tasks. In this case, the process Complexity factor can be considered in order to define the machine functional failure threshold. As the machine ages and its functionality deteriorates, the physical and cognitive effort required by the worker increases in order to maintain the production quality and volume. In this case, a complexity factor threshold can be defined such that when it is surpassed due to the increased required effort, the machine functionality should be restored.

#### 3- FAILURE FORMS

Two machine failure forms have been identified in the literature; sudden and gradual. Typically, sudden failure occurs randomly and its time of occurrence is modeled by an exponential distribution of a mean denoting the failure rate [15]. This model assumes that the system has two discrete states; operation and failure [16]. assumption is inapplicable to gradual failure where the system gradually experiences many states between the two extremes of operation and failure. Therefore, the traditional failure rate is not suitable for modeling it. It is suggested to model the gradual failure by a performance parameter of a value that timely represents the system functional status. Since the complexity is a measure of system functionality as early explained, it is proposed to model the gradual failure by the rate of complexity change, which is named "Complication Rate". This metric quantifies the machine/manufacturing system functionality deterioration per unit time. Assume that the Complexity at time t is C(t), then

complication rate, 
$$v(t) = \frac{dC(t)}{dt}$$
 (3)

And based on the developed complexity based failure definition, the failure occurs when the complexity reaches a threshold level, F. this condition is expressed

mathematically as 
$$\int_{0}^{t} \upsilon(t)dt = F$$
.

The total system failure rate would be function of the failure rate  $\lambda,$  the complication rate u and the failure threshold F. The total failure rate is not expected to be simply the summation of the sudden and gradual failure rates because in most real cases these two failure modes are dependent. Therefore; the total failure rate  $\lambda_{\rm T}$  would generally be expressed as:  $f(\lambda, \mathcal{V}, F)$  where the exact relationship is case-specific and its determination requires historical failure and performance data. This proposed new failure rate relationship captures all failure modes. The Complexity changes in sudden and gradual failures are illustrated in Figure (3).

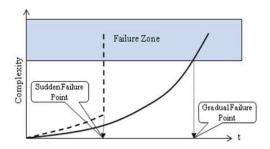


Figure 3 Complexity Change in Sudden and gradual Failure

Sudden failure is explained by the dotted line where complexity increases gradually with time till a random failure suddenly occurs, which causes a significant complexity increase that surpasses the specified failure threshold. This type of failure is modeled by the rate of failure occurrence or simply the failure rate ( $\lambda$ ). Gradual failure is modeled by the continuous line where the Complexity gradually increases until it surpasses the failure threshold, which causes system functional failure.

### 4- CASE STUDY

Ott et al. [17] introduced a case study of producing an "air-receiver magnetic assembly". Samples of size 5 were taken from the production line every shift. The depths of cut of 25 samples were collected (shown in Appendix A). According to the customer wants analysis, it was determined that the producing machine has one functional requirement; low deviation of the depth of cutting with a deviation design range of [-1, +1] mm. Traditionally, such a problem is analyzed using quality

control charts. Therefore, the  $\,X\,$  control chart will be constructed first. Then, the developed Complexity model will be used to analyze the same problem.

Ott *et al.* [17] constructed the  $\, X \,$  chart as shown in Figure (4) where the upper and lower control limits are:

UCL, LCL= 159.6616±3\*0.1343.

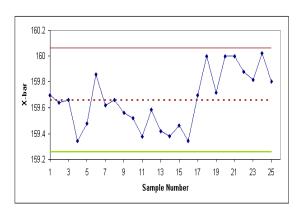


Figure 4  $\overline{X}$  Control Chart for the Depth of Cut

Analyzing this control chart according to Western Electric rules, [18] indicates that there is an out of control signal at sample 15. Therefore, a corrective maintenance action has to be performed to restore the machine functionality and bring it back to an in-control state. However, the control chart does not reveal any information about the machine functionality. Therefore, the control charts cannot be used to plan for preventive maintenance.

Using the same sample readings, the proposed Complexity-based functional failure metric application would be explained. The system range at each sampling point can be determined; assuming the samples are drawn from a normally distributed population and since the sample size is relatively small (5), then the samples readings follow the student t distribution. System range will be represented in Figure (5) at each sample point by a

line segment from X-3S to X+3S where S represents the sample standard deviation. The design range is represented by the shaded area in the deviation range [-1, 1]. Figure (5) illustrates the system range changes with time relative to the design range.

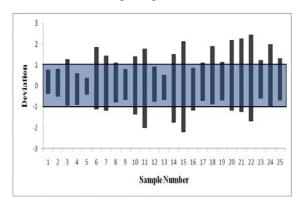


Figure 5 Change of system Range with time

This depiction shows any changes in either distribution mean or dispersion, which helps the decision makers understand the change in machine/ process functionality. Using these results, the machine complexity at each sampling point can be calculated using the following steps:

Step 1: calculate t values of upper and lower design range limits:

$$t_{U_i} = \frac{1 - \overline{X_i}}{S_i}$$

$$t_{L_i} = \frac{-1 - \overline{X_i}}{S}$$
(4)

Step 2: calculate the probability associated with the design range:

$$P_{i} = F(t_{U_{i}}) - F(t_{L_{i}})$$
 (5)

where F(t) is the student t distribution cumulative function

Step 3: calculate the machine functional complexity as follows:

$$C_i = -\log_2 P_i \tag{6}$$

The results of these calculations are shown in Figure (6). A linear regression analysis is performed to construct a Complexity trend line as shown by the straight line in Figure (6).

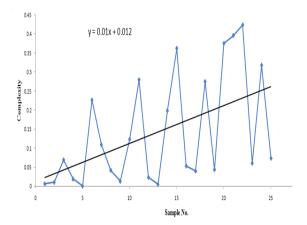


Figure 6 Complexity Change with Time

The regression analysis indicates that the Complexity can be modeled by the indicated equation where x represents the sample number (indication of sample time) and y represents complexity at the time of sample x. Since the samples are drawn from the production line at the beginning of each shift, then, the complication rate of this machine is 0.01 per shift. Therefore, assuming the machine failure threshold is set to be 0.1, then, the machine complexity is expected to exceed the pre-defined

threshold at 
$$\frac{0.1-0.012}{0.01} = 8.8$$
 shifts. Therefore, a

preventive maintenance should be planned before that time. Therefore, if this machine has a multi-level maintenance strategy, the duration between any two successive preventive maintenances should be less than 8.8 shifts. If the machine is in a plant that operates 2 shifts per day, 5 days per week, then the least preventive maintenance frequency is every 4.4 days ≈ 1 week.

# 5- SUMMARY AND CONCLUSIONS

A new model for defining functional failure is presented based on the complexity theory. Its main advantages are the formulation of a mathematical failure definition that is applicable to all failures types. The proposed model uses the machine Complexity as a measure of functionality and determines a failure threshold for Complexity. This threshold is case-specific and is determined by experienced decision makers as a trade-off between cost, quality and availability.

The "complication rate" term is introduced to measure machine functionality deterioration and gradual failure. It represents the rate of change of Complexity. The complication rate combined with the failure rate completely defines the machine failure behavior. This new approach of failure modeling captures and reveals the behavior of machine functionalities. It can be used to enhance preventive maintenance planning in order to keep desired machine functionalities above certain predetermined level/threshold.

The proposed novel complexity-based functional failure metric is applicable to individual products, machines and systems.

## **REFERENCES**

[1] Koren, Y., Heisel, U., Jovane, F., Moriwaki, T., Pritschow, G., Ulsoy, G., and Van Brussel, H., 1999. Reconfigurable manufacturing systems. CIRP Annals - Manufacturing Technology, 48(2): p. 527-540

- [2] Fashandi, A. and Umberg, T., 2003 Equipment failure definition: a prerequisite for reliability test and validation. in 28th International Electronics Manufacturing Technology Symposium. San Jose, CA, USA: IEEE.
- [3] Umeda, Y., Shimomura, Y., Tomiyama, T., and Yoshikawa, H., 1994. Design methodology for control-type self-maintenance machines. Seimitsu Kogaku Kaishi/Journal of the Japan Society for Precision Engineering, 60(10): p. 1429-1433.
- [4] Hajji, A., Gharbi, A., and Kenne, J. P., 2004. *Production and set-up control of a failure-prone manufacturing system.* International Journal of Production Research, 42(6): p. 1107-1130.
- [5] Jensen, W. A., Jones-Farmer, L. A., Champ, C. W., and Woodall, W. H., 2006. Effects of parameter estimation on control chart properties: A literature review. Journal of Quality Technology, 38(4): p. 349-364.
- [6] Umeda, Y., Tomiyama, T., Yoshikawa, H., and Shimomura, Y., 1994. Using functional maintenance to improve fault tolerance. IEEE Expert, 9(3): p. 25-31.
- [7] Umeda, Y., Tomiyama, T., and Yoshikawa, H., 1992 A design methodology for a self-maintenance machine. Edinburgh, UK: IEE.
- [8] Umeda, Y., Tomiyama, T., and Yoshikawa, H., 1995. Design methodology for self-maintenance machines. Journal of Mechanical Design, Transactions of the ASME, 117(3): p. 355-362.
- [9]. Grall, A., Dieulle, L., Berenguer, C., and Roussignol, M., 2006. Asymptotic failure rate of a continuously monitored system. Reliability Engineering & Engineering & System Safety, 91(2): p. 126-30.
- [10] Suh, N. P., 2001, Axiomatic Design, Advances and Applications: Oxford University Press.
- [11] Suh, N. P., 2005, Complexity, Theory and Applications, ed. MIT: Oxford University Press.
- [12] Lee, T., Complexity Theory in Axiomatic Design, in Mechanical Engineering. 2003, Massachusetts institute of Technology: Massachusetts. p. 182.
- [13] ElMaraghy, H. A., Kuzgunkaya, O., and Urbanic, R. J., 2005. Manufacturing systems configuration complexity. CIRP Annals Manufacturing Technology, 54(1): p. 445-450.
- [14] ElMaraghy, W. H. and Urbanic, R. J., 2004. Assessment of manufacturing operational complexity. CIRP Annals - Manufacturing Technology, 53(1): p. 401-406.
- [15] Ebling, C. E., 1997, An Introduction to Reliability and Maintainability Engineering: McGraw Hill.
- [16] Kenne, J. P. and Nkeungoue, L. J., 2008. Simultaneous control of production, preventive and corrective maintenance rates of a failure-prone manufacturing system. Applied Numerical Mathematics, 58(2): p. 180-194.
- [17] Ott, E. R., Schilling, E. G., and Neubauer, D. V., 2005, Process Quality Control. fourth ed: ASQ Quality Press.
- [18] Perry, M. B., Spoerre, J. K., and Velasco, T., 2001. Control chart pattern recognition using back propagation artificial neural networks. International Journal of Production Research, 39(15): p. 3399-3418.

## **APPENDIX A: CASE STUDY SAMPLES DATA [17]**

Cub	Sample	Sample	Sample	Sample	Campla
Sub- group	1	2	3	4	Sample 5
1	160.0	159.5	159.6	159.7	159.7
2	159.7	159.5	159.5	159.5	160.0
3	159.2	159.7	159.7	159.5	160.2
4	159.5	159.7	159.2	159.2	159.1
5	159.6	159.3	159.6	159.5	159.4
6	159.8	160.5	160.2	159.3	159.5
7	159.7	160.2	159.5	159.0	159.7
8	159.2	159.6	159.6	160.0	159.9
9	159.4	159.7	159.3	159.9	159.5
10	159.5	160.2	159.5	158.9	159.5
11	159.4	158.3	159.6	159.8	159.8
12	159.5	159.7	160.0	159.3	159.4
13	159.7	159.5	159.3	159.4	159.2
14	159.3	159.7	159.9	158.5	159.5
15	159.7	159.1	158.8	160.6	159.1
16	159.1	159.4	158.9	159.6	159.7
17	159.2	160.0	159.8	159.8	159.7
18	160.0	160.5	159.9	160.3	159.3
19	159.9	160.1	159.7	159.6	159.3
20	159.5	159.5	160.6	160.6	159.8
21	159.9	159.7	159.9	159.5	161.0
22	159.6	161.1	159.5	159.7	159.5
23	159.8	160.2	159.4	160.0	159.7
24	159.3	160.6	160.3	159.9	160.0
25	159.3	159.8	159.7	160.1	160.1