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FAULT DIAGNOSIS IN MACHINING BASED ON STATISTICAL PROCESS CONTROL

تشخيص أعطال عمليات التشغيل باستخدام خرائط الجودة الإحصائية

M. Adel El-Baz
Dept. of Industrial Engineering
Faculty of Engineering, Zagazig University, Egypt
E-mail: elbaza@mail2world.com

ملخص البحث

فى هذا البحث ، يتم إقتراح اسلوب لتشخيص أعطال عمليات التشغيل عن طريق خرائط الجودة الإحصائية ، وفى هذا الأسلوب يتم إستخدام المعلومات التى يتم تجميعها من خرائط الجودة فى إستنتاج مجموعة من القواعد التشخيصية والتى يتم تحديدها من الخبرات فى مجال التشغيل ورقابة الجودة فى تشخيص مشاكل عمليات التشغيل والتى ينتج عنها رفض نسبة من المشغولات وعن طريق التشخيص السريع لهذه المشاكل يمكن إكتشاف وإصلاح اسباب مشاكل الخلل فى العمليات الإنتاجية. والدراسة تم تطبيقها عن طريق تجارب وقراءات فعلية فى أحد خطوط الإنتاج لكباسات المبردات وتم عرض مثال تطبيقى لتأكيد كفاءة وفاعلية الأسلوب المقترح.

Abstract

In this paper, a fault diagnosis method based on statistical process control charts is proposed. The approach uses the knowledge extractions obtained from statistical process control charts and then extracts a set of minimal diagnostic rules by the experts in the field. The diagnosis performance of the proposed method is demonstrated using an experimental study. By means of the extracted knowledge, the machining process failures, and related rapid diagnosis can be identified. A practical system is presented to illustrate the efficiency and effectiveness of the proposed method.

Keywords: Statistical process control; machinability; fault diagnosis;

1. Introduction

High quality production provides some advantages such as reduced scrap or remachining and increased market share. For this purpose, quality should be achieved at every stage of production [1]. Statistical quality control is vital part of production. Instead of checking the finished product after production, it is applied at every period of production. If this period is under control, the next period is considered and the assignable causes are discovered and corrected.

There is considerable theoretical research work for improving product quality and process using statistical techniques [8]. Xie and Goh [16] discussed statistical techniques and their roles for process developed considering

Recent research works summarize design techniques by giving some examples. Optimization of process which is one of the important part of statistical process control was discussed in machining activities and the success

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of statistical process control was evaluated [4].

The impact of abnormal process operations is enormous both on safety and cost [14]. To ensure safety and stability, it is necessary to continuously monitor the process operations, detect and diagnose process abnormalities, and take appropriate remedial actions. Recently, due to the wide use of distributed control systems (DCS) or plant information systems (PIS) automated on line data collection has been popular. The availability of on-line data set has motivated the study of on-line fault detection and diagnosis [14, 9, and 15].

A fault is usually defined as abnormal process behavior associated with equipment failures or process disturbances. Typically a diagnosis system is provided with analysis of the observed inputs in order to identify a probable cause for a fault. The assignable root cause responsible for a fault can be identified [11]. The fault diagnosis of manufacturing systems refers to detect quickly the unacceptable part quality and the machine tool failure based on the information of production process and the knowledge of quality management. Statistical analysis of variation propagation is an effective way for fault diagnosis and efforts have been made in stream of variation modeling and its application [1-3, 6, 7, and 17] to identify the influences coming from both tooling errors and part errors. However, this modeling method is a very complex mathematical method.

A review of the research literatures on the diagnosability of dimensional variation and error compensation has been done by [10]. Hu and Koren [6] presented the stream of variation theory to predict and diagnose the dimensional variation in a multi-leveled automotive body assembly system. Huang et al. [7] proposed a systematic diagnostic methodology to monitor process and determine root causes of quality-related problems for machining processed. Ceglarek et al. [3] introduced a state space model and developed fault diagnosis method based on the model for assembly system.

Barhak et al. [2] presented an advanced quality control methodology for reconfigurable manufacturing systems. It enables rapid root-cause diagnostic for faster ramp-up of reconfigurable systems through integration of the reconfigurable inspections machine. The above methodologies are very complex and the modeling is not an easy task and increases dramatically with the system size.

Artificial Intelligence (AI) for fault diagnosis has been developed increasingly, which provide greater ability to deal with the natural complexity of manufacturing process in fault diagnosis. These approaches includes rule-based system, model based system, case-based system and neural network [13]. In this paper, a fault diagnostic method based on statistical process control charts and ruled-based system is proposed. In the paper, section 2 describes the framework of the proposed method. Section 3 describes the rule-based fault diagnosis system including the statistical process control charts and the experimental results for the rule-based needed for faults decision. Section 4 presents the fault diagnosis system implementation. Section 5 is the conclusion.

2 – Framework of the proposed system

This paper proposes the integration of diagnosis and decision taking knowledge with process monitoring in a production line platform. A schematic diagram in figure 1 shows the basic components of the proposed system.

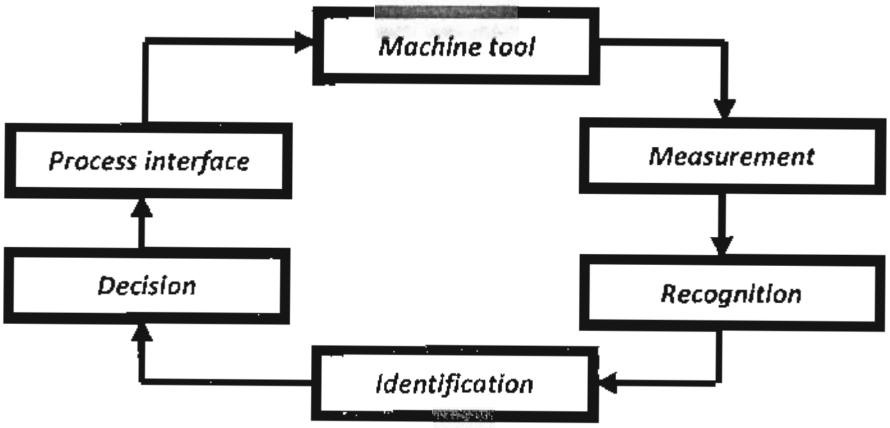

Figure1. Basic Components of The rule-base fault diagnosis system

More specifically, when an out-of-control state is detected, the fault data are transmitted with a group of fault patterns. Then, a pattern matching is performed to compare the on-line fault library. The similarity between two fault patterns is detected for each cause candidate. Finally, a diagnostic decision is made as the assignable cause. Figure2 illustrates the framework of the proposed method.

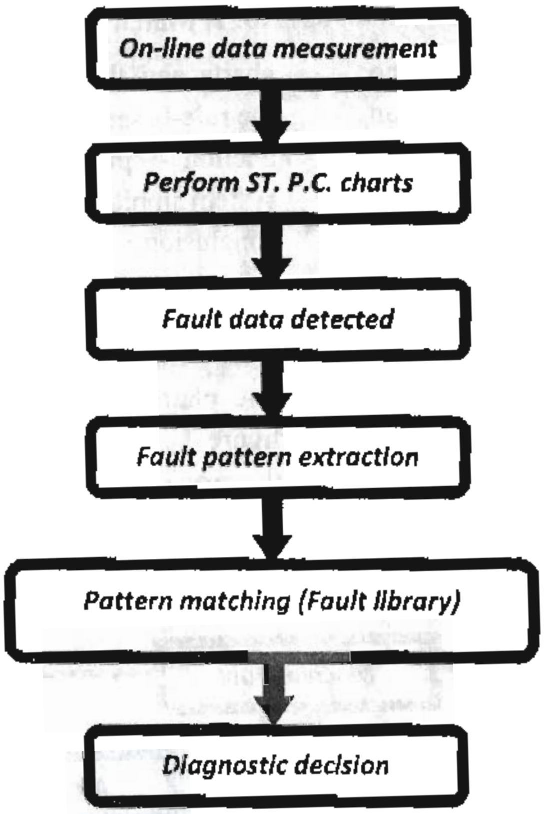

Figure 2 Framework of the proposed method

3-1. Statistical Process Control

Control charting is one of the tools of statistical quality control (SQC). It was developed in the 1920 s by Dr. Walter A. Stewart. He developed it to study manufacturing process variation for the purpose of proving the economic effectives of the process. There methods are based on continuous monitoring of process variation, a typical control chart is a graphical display of a quality characters that has been measured or computed from a sample versus the sample number or time. The theoretical base of SPC is the central limit theorem and 3 σ principal [12].

The chart contains a center line that represents the average value of the quality characteristic corresponding to the in-control state. Two other horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL) are also drawn. These control limits are chosen so that if the process is in control, nearly all of the sample points will fall between them.

As long as the points plot within the control limits, the process is assumed to be in control, and no action is necessary. However, a point that plots outside of the control limits is interpreted as evidence that the processes is out of control and investigation and correction action is required to find and eliminate the assignable causes responsible for this behavior. The control points are connected with straight line segments for easy visualization. Even if all the points plot inside the control limits, if they behave in a systematic or nonrandom manner, then this is an indication that the process is out of control.

The manufacture usually adapts X and R control chart, where the control lines of X chart and R chart are computed as the following methods:

X chart:

$$UCL=\bar{\bar{x}}+E\bar{R} \quad (1)$$

$$CL=\bar{\bar{x}} \quad (2)$$

$$LCL=\bar{\bar{x}}-E\bar{R} \quad (3)$$

R chart:

$$UCL=G_1\bar{R} \quad (4)$$

$$CL=\bar{R} \quad (5)$$

$$L=G_2\bar{R} \quad (6)$$

Where

$$\bar{\bar{x}}=\frac{1}{n}\sum_{i=1}^{n}[\frac{1}{m}\sum_{j=1}^{m}l_{ij}] \quad (7)$$

$$\bar{R}=\frac{1}{n}\sum_{i=1}^{n}(l_{imax}-l_{imin}) \quad (8)$$

l is the controlled size of parts, m is the sample size, n is the number of sample groups, and E, G_1, and G_2 are constants (obtained from coefficient table for the controlling diagram with measuring values). The alarms of SPC control chart can be divided into the following reasons:

1. Sample points outside of process control limits.
2. Points are cyclic fluctuated.
3. Continuous 7 points above or below average.
4. Continuous 7 points go or down
5. Most points near control limits.

When one of the previous situations are present in the SPC chart, it shows that there are abnormal fluctuations of some process variables that influenced product quality.

3.2 Rule-Based faults diagnosis system

Rule-based is used to solve the practical problem of fast fault diagnosis system. When the SPC control charting indicates that there are abnormal quality data, then the extracted rule-based system will be used to diagnose faults. The ideas of this concept are as follows: The initial process measured data are read from the SPC control charting alarm points.

- By matching the antecedent of each rule, the available knowledge set is constructed.
- Continue the solution process and recording new facts will result in extract new knowledge of the database rule sets.
- Repeat these procedures to update the database set rules and enhance the fault diagnosis system.

3.3 Experimental results and formation of decision rules

The multistage production line of refrigeration hermetic compressor is taken as an example. The production line found at Misr Compressors manufacturing company which is an Egyptian joint stock company. Its authorized capital is LE 350 million paid up LE 210 million. Maximum production capacity 2 millions compressors per year based on two shifts per day- 20 hours per day. The experimental results include two main parts of the compressor, the piston and the crankshaft. Figures 3 and 4 illustrate the measured dimensions of the two parts. The required dimensions are obtained from the successively machining process and the data recorded in a data sheet. If the dimension is eventually checked to be disqualified, the corresponding error cause is recorded to construct the rule-base faults diagnosis decision. The extracted decision rules are presented in Table 1.

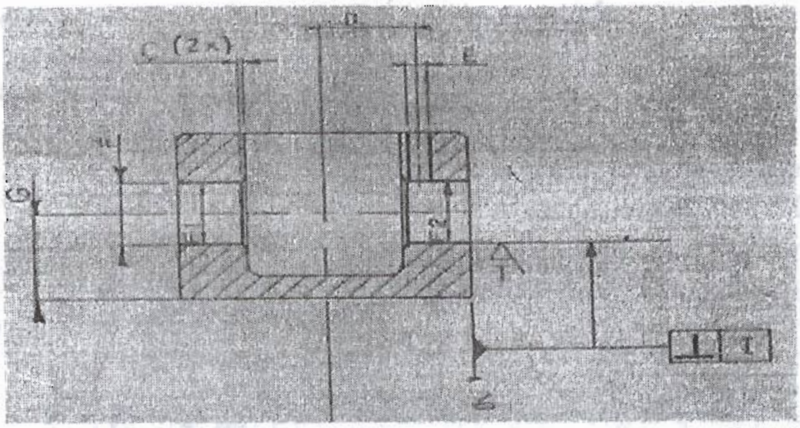

Figure 3. Measured dimension of piston

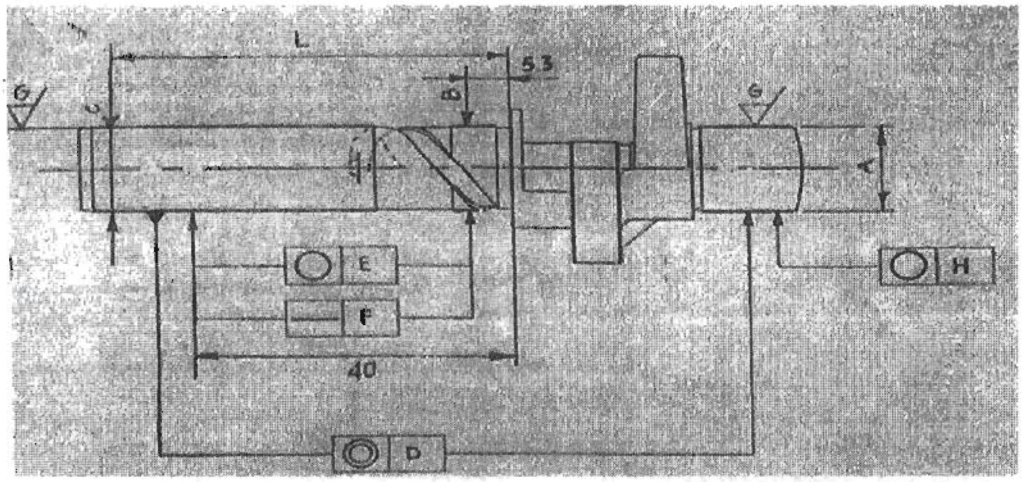

Figure 4. Measured dimension of crankshaft

Table 1. Decision rules (x-bar chart pattern and corresponding failure)

Rule	Pattern	Failure Cause
1	One or two points of sample points outside of process control limits. (Figure 5. a)	Chip formed on part during machining
2	Sample points outside of process control limits (Figure 5. b)	Disqualification of outsourced parts
3	Sample points are cyclic fluctuated and most points near control line. (Figure 5. c)	Coolant liquid problem
4	Sample points are cyclic fluctuated and points not near control line. (Figure 5. d)	Location or adjustment errors of fixture
5	Continuous 7 points go or down. (Figure 5. e)	Cutter abrasion
6	Continuous 7 points above or below average. (Figure 5. f).	Unbalance of machining allowances (compensating of machine setting required

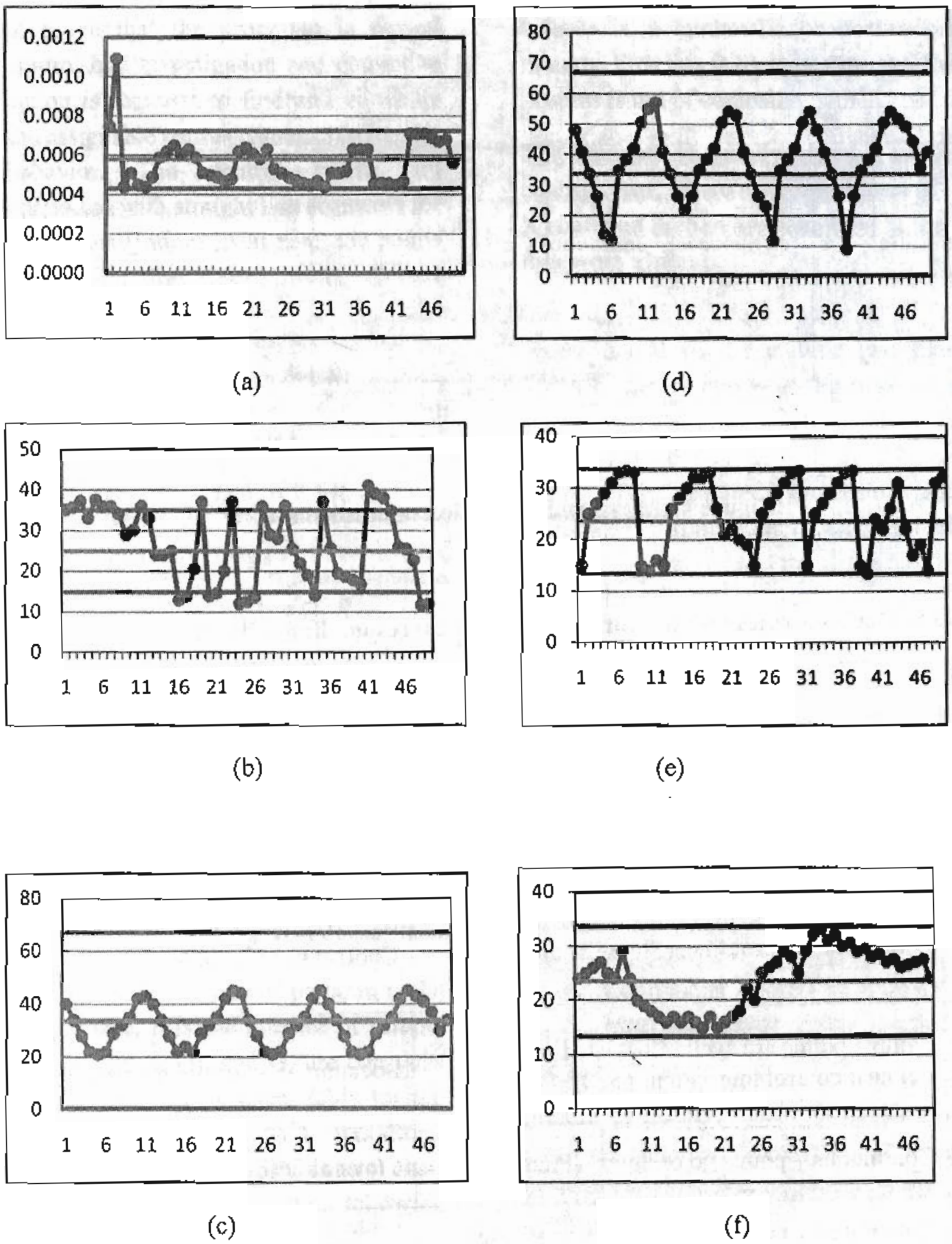

Figure 5. X-bar control charts extracted patterns

4. Case Study

Software is designed to collect measuring data and figure out real time c-bar charts. Then, through identifying the characteristics value and searching for corresponding rules in rule base, the error source can be traced. The following example illustrates the on-line implementation of the system. It is shown in Figure 6 that there are sample points outside the process control limits and by matching the second rule in Table1, the diagnosis results can be directly obtained, showing that there exists disqualification of the outsourced part. After careful inspection, it is discovered that there exists some lines of cracks of the raw materials affect increasing cutting force in machining process and consequently, increasing the vibration and result in points outside of process control limits.

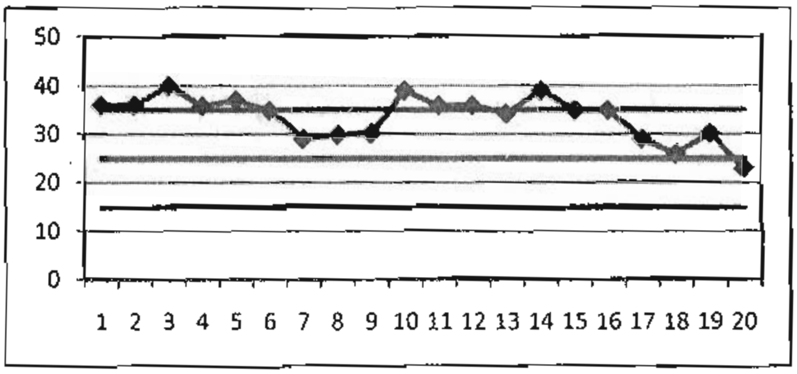

Figure 6 x-bar control chart for the application example

5. Conclusion

Rapid diagnosis of dimensional failures in machining is of critical concern. In the paper, a fault diagnosis method in machining based on rules extracted from statistical process control charts is presented. The approach uses the knowledge extractions that are obtained from statistical process control charts, and then extracts a set of minimal diagnostic rules by the experts in the field. By means of knowledge acquisition, the machining process failures in machining can be then identified. The extracted rules and the diagnosis performance are performed and tested through industrial experimental case study in the key process of compressor production line. Test result has been verified the effectiveness and efficiency of the proposed method.

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