Implementation of an AI-based forging equipment failure diagnosis system

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Summary

Forging equipment has advanced in recent years to support fully automated production, making control systems more complicated. This has required more time for identifying the causes of equipment failures when they occur. Therefore, artificial intelligence (AI) was used to develop an equipment failure diagnosis system that converts the tacit knowledge possessed by veteran maintenance personnel into explicit knowledge. This article describes the system that has been implemented to reduce the time needed for diagnosing the causes of failures.

1. Introduction

Progress has been made in recent years in fully automating the transport devices of forging equipment to achieve high-efficiency production. For that reason, control systems have become more complicated than those of previous equipment, making it more difficult to pinpoint the true cause of a failure when one occurs. The failure diagnosis procedures used by maintenance personnel to repair failures and their failure diagnosis time vary depending on the knowledge and skills of each individual.

This article describes an equipment failure diagnosis system that has recently been created in which artificial intelligence (AI) was used to incorporate the tacit knowledge, i.e., skills, know-how and experience, of veteran maintenance personnel. This system has proved to be effective in shortening the mean time to repair (MTTR).

2. Present status

2.1 Present status of forging equipment

Figure 1 shows MTTR data for assembly, casting, machining and forging equipment. It takes more time to repair and restore forging equipment compared with assembly, casting and machining equipment.

Figure 2 shows a percentage breakdown by task of the MTTR for forging equipment. The percentages indicate that diagnosis time is the next longest task after recovery time.

Progress was made in automating assembly equipment beginning from the 1990s. The equipment composition was established, and accumulated data and skills have been reliably handed down to support short diagnosis times.

In contrast, automation of forging equipment has advanced rapidly in the past decade or so. Existing large-scale forging machines were automated and connected by transport devices to form the forging line. Along with the increased complexity of the control system, the causes of failure also vary widely. Consequently, one factor causing longer MTTR for forging equipment is that differences in the skill levels of maintenance personnel are clearly reflected in their diagnosis time.

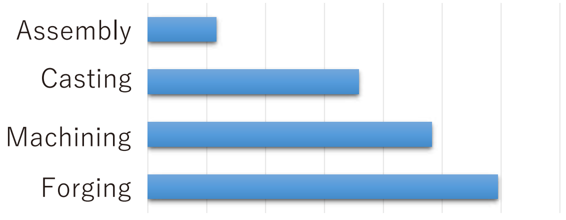

Fig. 1 Analysis of mean time to repair (MTTR)

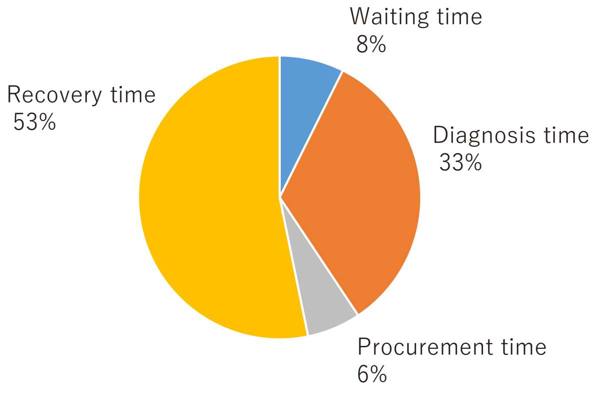

Fig. 2 Percentage breakdown by task of MTTR for forging equipment

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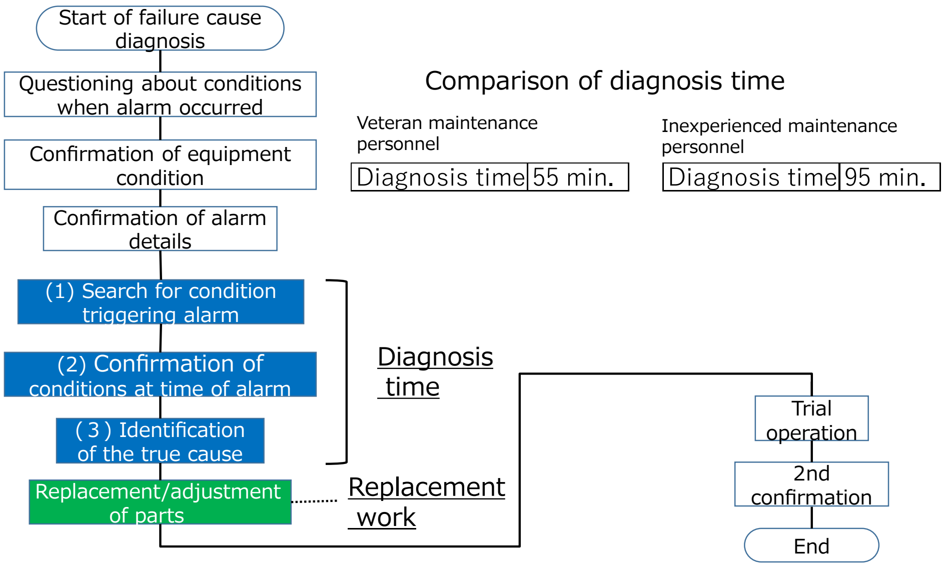


Fig. 3 Flow of failure recovery

2.2 Failure recovery method

Figure 3 outlines the flow of the failure recovery method used by maintenance personnel. The results of an analysis of the failure recovery time of veteran and inexperienced maintenance personnel revealed that their diagnosis time differed by 40 minutes.

A survey was conducted to clarify the reasons for the difference in diagnosis time between veteran and inexperienced maintenance personnel. Veteran maintenance personnel were interviewed concerning their failure diagnosis procedures, and a comparison was made with inexperienced maintenance personnel regarding the following three perspectives to clarify what was different between the two groups.

(1) Search for the condition triggering an alarm

When veteran maintenance personnel arrive at the site of a problem, they check the condition of the equipment and alarm details and consider whether a similar situation occurred in the past. On that basis, they propose candidates as possible causes of the failure. It was found that the number of their candidates differed from that of the inexperienced maintenance personnel.

(2) Confirmation of conditions when an alarm occurs

Veteran maintenance personnel carefully observe and remember the normal operating conditions of equipment on a regular basis. In diagnosing a failure, they operate the equipment and reproduce the conditions at the time an alarm occurred. By comparing the operation and signals with the normal conditions, they narrow down the candidates for the possible cause of the failure. The time taken to narrow down the candidates differed from that of the inexperienced maintenance personnel.

(3) Identifying the cause of a failure

It was found that veteran maintenance personnel perform a mental why-why analysis in the process of using the methods in (1) and (2) above and quickly identify the cause of a failure based on rules and principles. Their accuracy in identifying the causes of failures also differed from that of the inexperienced maintenance personnel.

Therefore, in order to close the gap in diagnosis time due to the skill levels of maintenance personnel, it was decided to build a model line and develop an equipment failure diagnosis system.

3. Development of an equipment failure diagnosis system

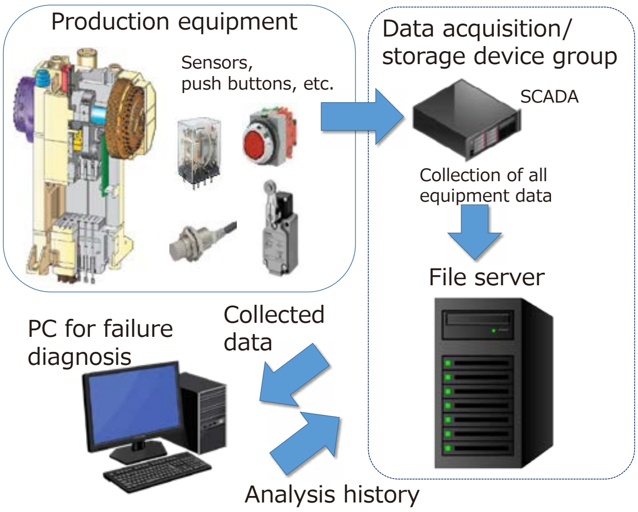
3.1 Development aim

The purpose of this equipment failure diagnosis system is to enable anyone to perform a failure diagnosis equal to that of veteran maintenance personnel in a short period of time. Accordingly, anyone who uses this system can efficiently acquire the knowledge and skills possessed by veteran maintenance personnel.

3.2 System configuration

The system uses AI to learn the normal equipment operating conditions so that it can automatically identify the cause of a failure when an alarm occurs.

Figure 4 shows the system configuration, which can be broadly divided into two sections. One is a data acquisition/storage device group consisting of a Supervisory Control and Data Acquisition (SCADA) system for collecting operating condition data in real time, mainly by means of sensors attached to the equipment and push buttons, and a file server for storing the data. The other is a PC equipped with an AI program for performing a failure analysis using the data stored in the server. The PC performs the data exchanges, learning and analysis.



SCADA (Supervisory Control and Data Acquisition)
This computer system provides remote centralized monitoring and control at one location of various production machines at the plant and elsewhere. It collects and centrally records data from sensors and other devices.

Fig. 4 System configuration

3.3 Method of learning normal operating data

In order for the system to learn the normal equipment conditions, the AI-equipped PC for failure analysis reads operating data from the file server when no alarms have been issued.

Calculating and learning large volumes of device data every time would put an enormous load on the CPU of the PC for failure analysis. To avoid that, Welford's method was used to perform mean and variance calculations. This calculation method repeats a procedure whereby the difference from the previous data is calculated and reflected in a cycle diagram as the standard deviation. An example of a learned cycle diagram is shown in Fig. 5. In one cycle of a cycle diagram, the system learns the data from all the acquisition devices that number approximately 8,000 in total, including sensors, push buttons and others. The system learns the time-history data and timing and records the standard deviation and the current data as waveforms.

As one example, the equation for calculating the mean with Welford's method is shown below.

$$\mu_n = \frac{1}{n}\sum_{i=1}^{n} x_i$$

The recurrence relation of the equation above is expressed as:

$$\mu_{n+1} = \frac{1}{n+1}(x_{n+1} - \mu_n) + \mu_n$$

μ_{n+1}: updated mean
μ_n: mean calculated the previous time
x_{n+1}: newly obtained collected data
n: number of collected data

3.4 Database of individual causes of failure

In order to quickly and accurately identity failure causes, it is essential to create in advance a database containing the causes of failures that have occurred previously. A failure history list was made, and a database of individual failure causes was created that summarizes the time when alarms occurred, the device causing each failure and other details.

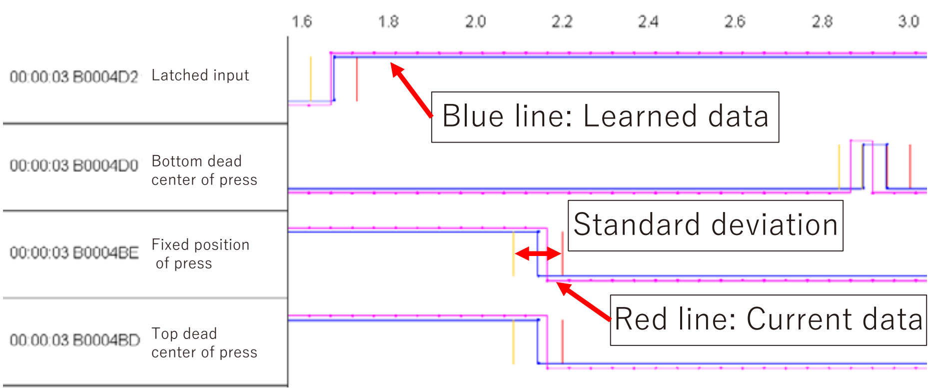


Fig. 5 Learning screen of a cycle diagram

3.5 System for failure diagnosis

The instant an equipment alarm occurs the present cycle diagram is cut into sections and a comparison is made of the sectioned current cycle diagram and the previously learned cycle diagram. Devices showing a mean exceeding $\pm 3\sigma$ among all the device data are narrowed down as failure cause candidates.

The narrowed down candidates are cross-checked with data in the database for individual failure causes, and a matching device is identified as the cause of the failure. If multiple matching devices are found, the time when the alarm occurred is cross-checked with the database and a matching device is identified as the failure cause.

3.6 Effectiveness of AI-based failure diagnosis system

It has become possible to narrow down failure cause candidates by teaching the system the normal operating conditions of the equipment and making a comparison with the cycle diagram when an alarm occurs.[1] In addition, the accuracy of judgments for identifying failure causes has been improved by drawing upon the knowledge of veteran maintenance personnel.

The implemented system can search for the cause of a failure in the shortest diagnosis time possible without being influenced by the skill levels of maintenance personnel. Figure 6 shows the effect of the system on reducing diagnosis time following its implementation.

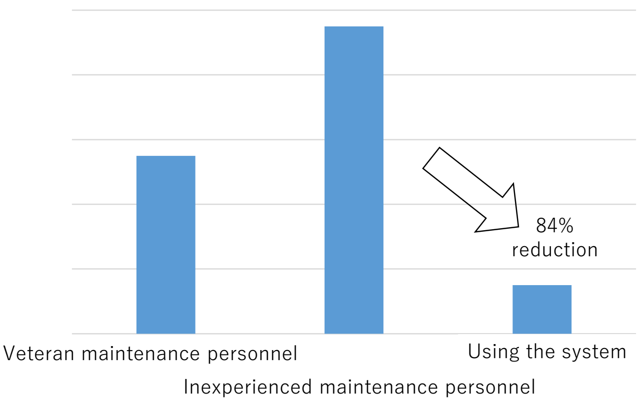


Fig. 6 Effect on improving diagnosis time

The newly developed system uses AI to automate the skills that veteran maintenance personnel possess for narrowing down candidate failure causes. This capability markedly shortens the time needed for identifying the cause of a failure by eliminating the need to operate the equipment and to reproduce the conditions present when an alarm occurs.

As a result, using this AI-based failure diagnosis system has reduced failure diagnosis time by 84%.

4. Future issues

An analysis of the methods used by veteran maintenance personnel to diagnose failures revealed the logic that maintenance personnel have traditionally applied in diagnosing the causes of failures. That made it possible to convert the tacit knowledge of veteran maintenance personnel into explicit knowledge.

It is planned to deploy this system horizontally on other production lines in the future and also to use it to improve maintenance personnel educational methods that have been practiced heretofore.

5. Reference

(1) Yoshi Sano, Optimization of Rolling Conditions by Microsecond Analysis using ICT, Plant Engineer, Japan Institute of Plant Maintenance, Vol. 53, No. 12 (in Japanese).

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