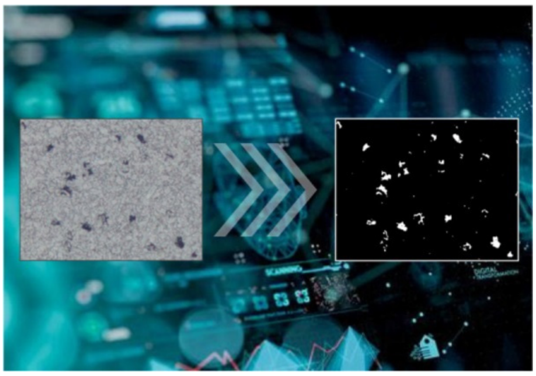
Remaining Life Assessment Service of High Strength Ferritic Heat Resistant Steel Piping Weld Utilizing Image Analysis by AI



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Mitsubishi Heavy Industries, Ltd. (MHI) has developed and provided customers with various after-sales maintenance services for equipment maintenance necessary for the stable operation of plant facilities. However, problems such as experienced service technicians and experts retiring are expected to become more serious in the future, so it is necessary to establish a system for providing services that do not depend on human workers. As a measure to address this issue, we have developed a remaining life assessment service of plant piping welds using AI-based image processing. Providing customers with the information necessary for maintenance planning more quickly and accurately than ever before using this service will lead to appropriate equipment maintenance, which in turn will contribute to ensuring the reliability of plant equipment over the medium to long term and the stable supply of electricity.

1. Introduction

Many of the large plant facility products we provide, such as power generation plants and chemical plants, are used for several decades after delivery to customers. To ensure that our customers can use and operate such products with peace of mind for a long time, it is necessary to fully exploit their performance and improve their reliability, for which appropriate equipment maintenance is indispensable. Based on our abundant product knowledge and experience, we have developed and offered after-sales maintenance services for equipment maintenance to our customers. The types of such services, which vary depending on the product, a remaining life assessment service of piping [(1)], a non-destructive inspection and evaluation service [(2)], and a remote monitoring and abnormality diagnosis service [(3)].

On the other hand, the recent concern about maintenance in plant facilities is that many plant facilities are becoming older [(4)], and the importance of facility maintenance is expected to further increase. In addition, problems of technology transfer and labor shortages due to the retirement of experienced workers with abundant expertise have become apparent [(4)]. MHI is no exception to this, and we urgently need to maintain and improve the level of after-sales maintenance services that have been provided by experienced service technicians, engineers, and experts. Thus, in order to continuously provide customers with after-sales maintenance services related to equipment maintenance, which will become more important in the future for the stable operation of plant facilities, the early establishment of a system that does not depend on the competence and experience of human workers is one of the challenges we need to address.

As a measure to address this issue, MHI is working on quality assurance and automation of after-sales maintenance services by utilizing AI (Artificial Intelligence), which has benefited from the knowledge and know-how of experienced workers and experts, as well as robots that work in place of humans. This report describes an AI technology developed for remaining life assessment of high-strength ferritic steel piping welds and a life assessment service using this technology as an example of our efforts on remaining life assessment required for CBM (Condition-Based

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Maintenance), which is one of the most important equipment maintenance methods.

2. Creep damage occurring in high-strength ferritic steel piping welds and remaining life assessment

First, this chapter describes the high-strength ferritic steel piping welds to be remaining-life assessed described above and the creep damage that occurs therein. High-strength ferritic steel, one of the materials that supports high efficiency power plants, is also called high-strength ferritic heat-resistant steel or CSFE (Creep Strength Enhanced Ferritic) steel. It is a generic term for ferritic steel with high creep strength due to highly controlled martensitic or bainitic microstructure stabilized by carbides, carbonitrides, or other stable or metastable phases with high tempering resistance [5]. High-strength ferritic steel is used for main piping and heat transfer tubes in USC (Ultra-Super-Critical) boilers and piping in nuclear power plants. These piping and heat transfer tubes are used for long periods of time in high-temperature, high-pressure environments, resulting in creep strength degradation and creep damage due to changes in microstructure over time. Especially in fine grained HAZ (Heat-Affected Zone) of welds, where the creep strength is lower than that of the base metal, creep damage is likely to occur [6]. **Figure 1** shows a conceptual diagram of general creep damage behavior. In the initial stage of creep damage, microstructural changes such as precipitate agglomeration, coarsening, and dislocation density reduction occur. However, after the middle stage, creep strain tends to accumulate along with the microstructural changes, and creep voids are preferentially generated at the grain boundaries with the accumulation of creep strain, which increase and coalesce to form creep cracking. The creep damage has a correlation between the void number density, which indicates the number of voids in a certain area, and the creep rupture life consumption rate. Using this correlation, a method to assess creep life consumption rate from the void number density is called the void number density method [1] (**Figure 2**).

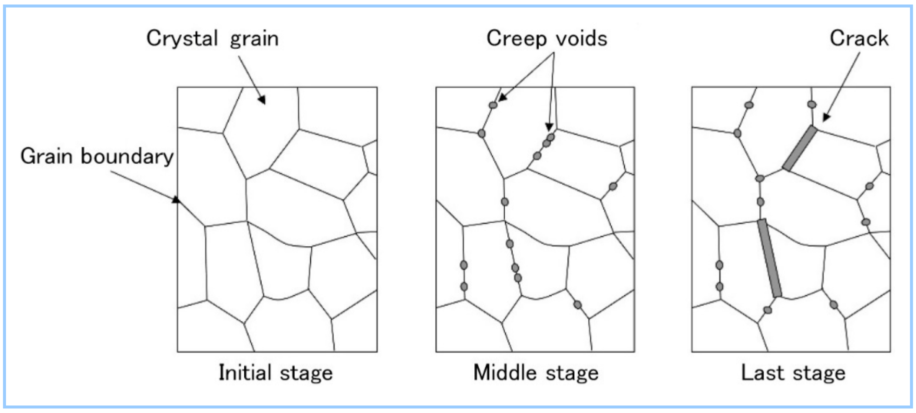

Figure 1 General progression of creep damage and generation/growth of voids

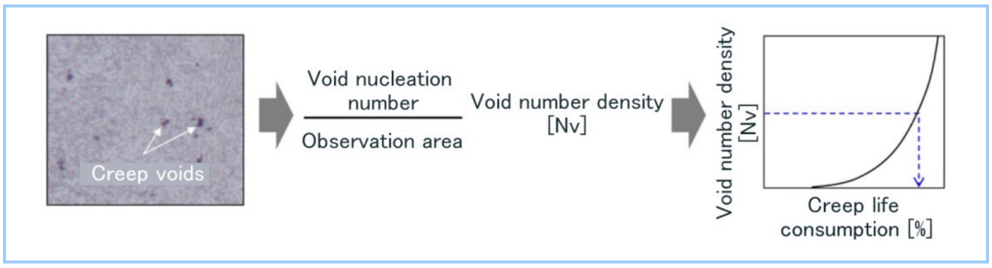

Figure 2 Conceptual diagram of life assessment using void number density method

3. Conventional technology and problems

The void number density is calculated by an expert observing the microstructure taken from the metal surface by the replica method under a microscope and counting the voids one by one (**Figure 3**). However, there are a limited number of experts who can evaluate the void number density from the microstructure image, and the evaluation process is time-consuming, which are apparent problems. In response to this, we have developed image processing technology with an algorithm reflecting the knowledge of experts in identifying voids for low alloy steel, which were widely used before the emergence of high-strength ferritic steel, and established a semi-automated life assessment method using the void number density method. This method has already been used in a great number of cases [7]. This image processing algorithm uses image features such as the circularity, area, aspect ratio, and brightness of voids as indices for void identification, and can automatically identify voids in the HAZ of low alloy steel from the same viewpoint as experts by setting the optimal parameters based on the expert's knowledge (**Figure 4**). **Figure 5** shows an example of void images generated in the HAZ of low alloy steel and in the HAZ of high-strength ferritic steel. Although these are only examples, the void shapes of high-strength ferritic steel are more complex than those of low alloy steel. Therefore, it is difficult to identify voids in high-strength ferritic steel using the image processing algorithm for low alloy steel. Experts had to assess the void number density and remaining life of high-strength ferritic steel one by one manually.

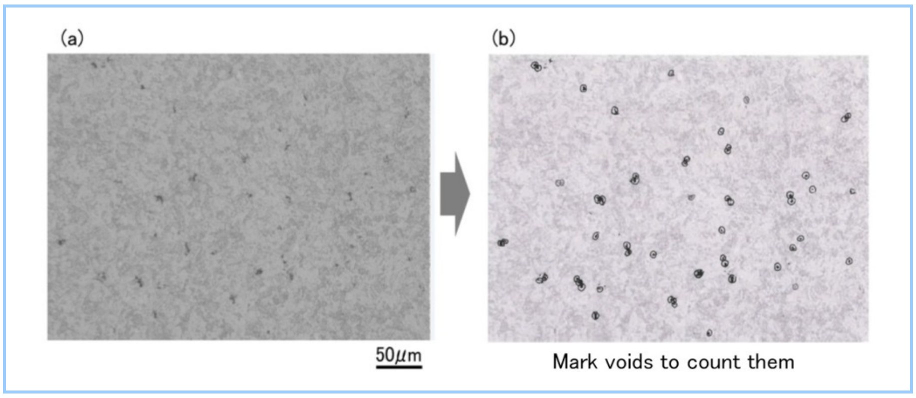

Figure 3 Example of void identification by expert
(a) Observed image, (b) Void marking result

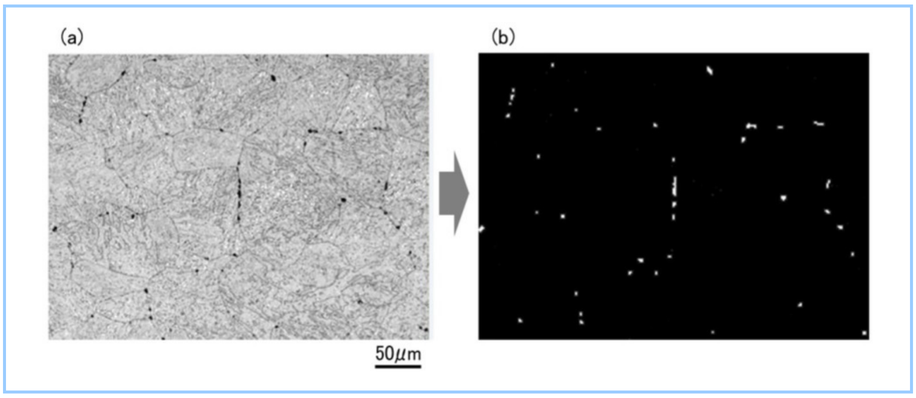

Figure 4 Examples of voids occurring in HAZ of low alloy steel and image processing
(a) Non-labeled image, (b) Voids-identified image

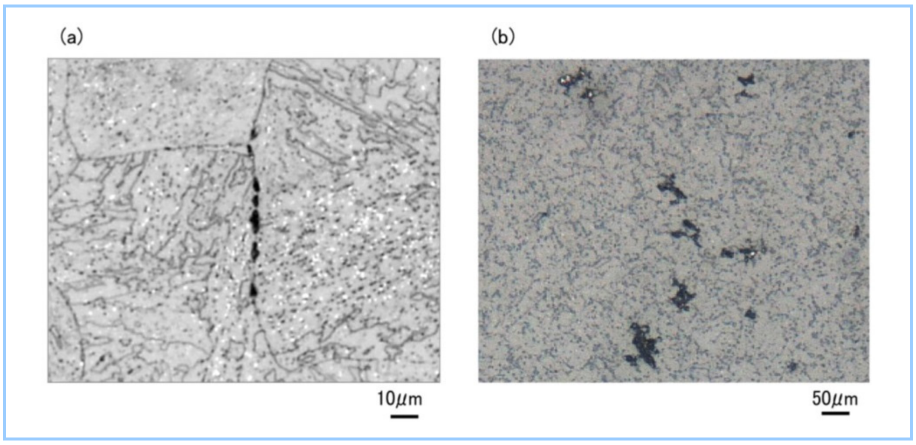

Figure 5 Comparison of void shapes between low alloy steel and high-strength ferritic steel
(a) Low alloy steel, (b) High-strength ferritic steel

4. Application of image processing technology using label correction AI

We attempted to apply AI technology, which has attracted a lot of attention in recent years, to the identification of voids in high-strength ferritic steel, which is difficult to do with image processing focusing on general image features such as the circularity and area of voids. There are many AI-based methods for identification on material microstructure images, and one such method is known as segmentation [(8)]. In the case of void images, it is necessary to identify void areas from background microstructure images and contamination (e.g., contaminants from replica collection), so instance segmentation is considered to be effective. However, preparing an image identifier using instance segmentation requires a large number of labeled (annotated) teacher images, which can be very time-consuming and costly (**Figure 6**).

As such, MHI focused on the teacher label correction technology [(9), (10)], which can generate a large number of labeled images from a small number of simply labeled images and a large number of non-labeled images, and attempted to build a void image identifier for high-strength ferritic steel by using this technology (**Figure 7**).

Section 4.1 and Section 4.2 describe the procedures and results of the applicability verification tests of the above-mentioned technology.

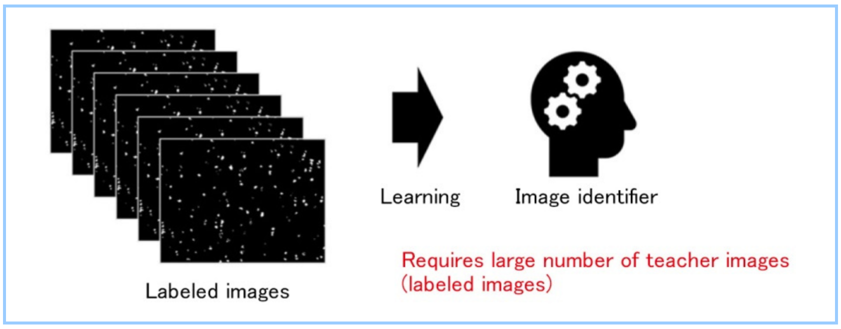

Figure 6 Problem of general image learning

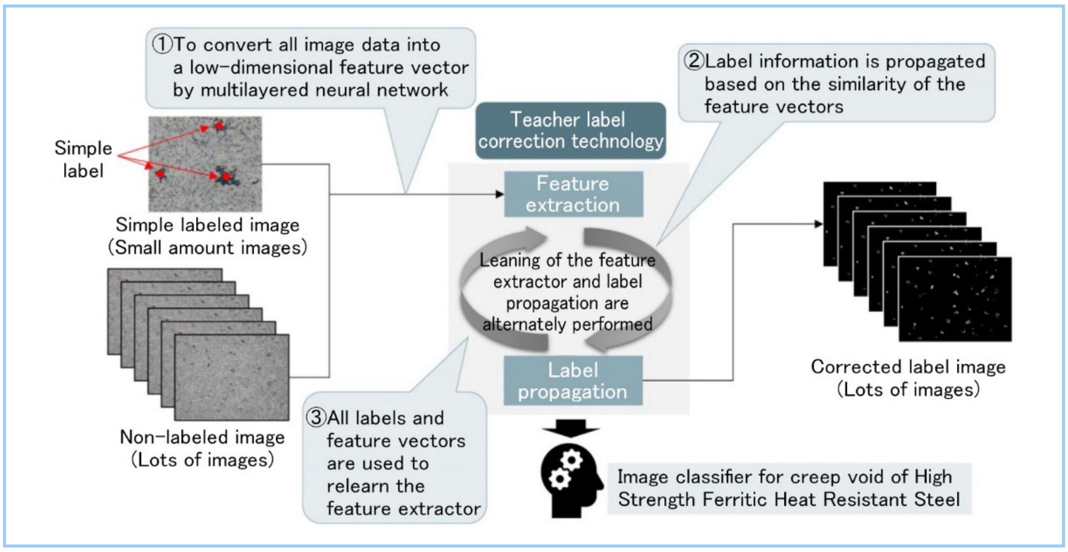

Figure 7 Building image identifier for high-strength ferritic steel voids using teacher label correction technology

4.1 Test procedures

In this test, among high-strength ferritic steel, Grade 91 steel (KA-STPA28, etc.), Grade 122 steel (KA-SUS410J3TP, etc.), and Grade 23 steel (KA-STPA24J1, etc.), which have been widely used in piping and heat transfer tubes for boilers in Japan, were selected as the testing targets. **Table 1** shows information on the image data used for learning. The teacher label correction technology basically uses non-labeled images and simply labeled images for learning, but in this test, labeled images were partially used for learning in order to improve the accuracy of the identifier. Moreover, image segmentation was used as pre-processing for learning these images. As a result, the actual number of images used for learning is larger than that shown in Table 1, but the number of labeled images created is the same. The images in Table 1 were processed according to steps ① through ③ shown in Figure 7, repeating label propagation and feature extractor learning alternately until a corrected labeled image with a high percentage of correct responses was generated. The index of correctness was defined as IoU (Intersection over Union), which is used as a measure of object detection on images, and we defined that the IoU of 0.6 or higher indicates accurate identification of voids based on the IoU of correct images created by experts and other data.

Table 1 Image data used for learning

Tested steel type	Number of images used for learning		
	Original image	Simply labeled image	Detail labeled image
Grade 91 (9Cr-1Mo-V-Nb)	140	9	13
Grade 122 (11Cr-0.4Mo-2W-Cu-V-Nb)	91	42	3
Grade 23 (2.25Cr-1.6W-V-Nb)	75	0	0
Total	306	51	16

* Indications in parentheses are basic components.

4.2 Test results

Figure 8 shows a representative example of the identification results of a non-labeled image (original image) using the identifier built by the above procedures. Although the voids in this image have complex shapes, the IoU of the voids-identified image is 0.72, indicating that the identifier is able to identify the voids with high accuracy. Some no-void locations were mistakenly identified as voids, but, in such cases, experts can correct the images by using the painting tool as described below to achieve the evaluation accuracy of IoU and void number density equivalent to that of the experts.

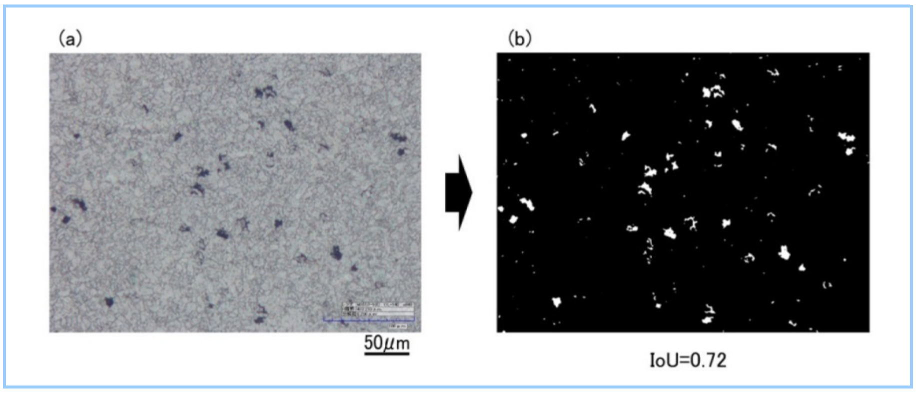

Figure 8 Example results of image identification using label correction AI (a) Non-labeled image, (b) Voids-identified image

5. Value provided by life assessment service

Utilizing the identifier built in this time, we developed a system that can evaluate the void number density and the life of high-strength ferritic steel piping welds. **Figure 9** shows the work procedures of the conventional life assessment method by an expert and by this system. In the conventional method, all the work is performed by an expert. This system is capable of automatically evaluating the void number density and life consumption rate from images automatically identified by the AI and corrected by an expert using a paint tool on GUI (Graphical User Interface) as necessary. **Figure 10** shows the results of the evaluation of the life consumption rate from the void images of Grade 23 steel using this system. The vertical axis in the figure shows the results of life assessment rate by experts, and the horizontal axis shows the results of life assessment rate by this system using AI. The assessment results by the AI agreed well with those of the experts [(11)]. **Figure 11** compares the time required for the remaining life assessment between the conventional method by two experts and the new method using the above system. It is indicated that the new method can reduce the assessment time by approximately 80%.

As a result of the study described above, by utilizing AI for after-sales maintenance service operations that assess remaining life based on void images, it is possible to provide customers with services of the same quality as the assessment services conventionally provided by experts in a shorter time than before, while reducing dependence on such experts. We believe that providing customers with the remaining life assessment results necessary for medium- to long-term facility maintenance planning more quickly and accurately than before will lead to appropriate facility maintenance, which in turn will contribute to ensuring the reliability of plant facilities and a stable supply of electricity over the medium to long term.

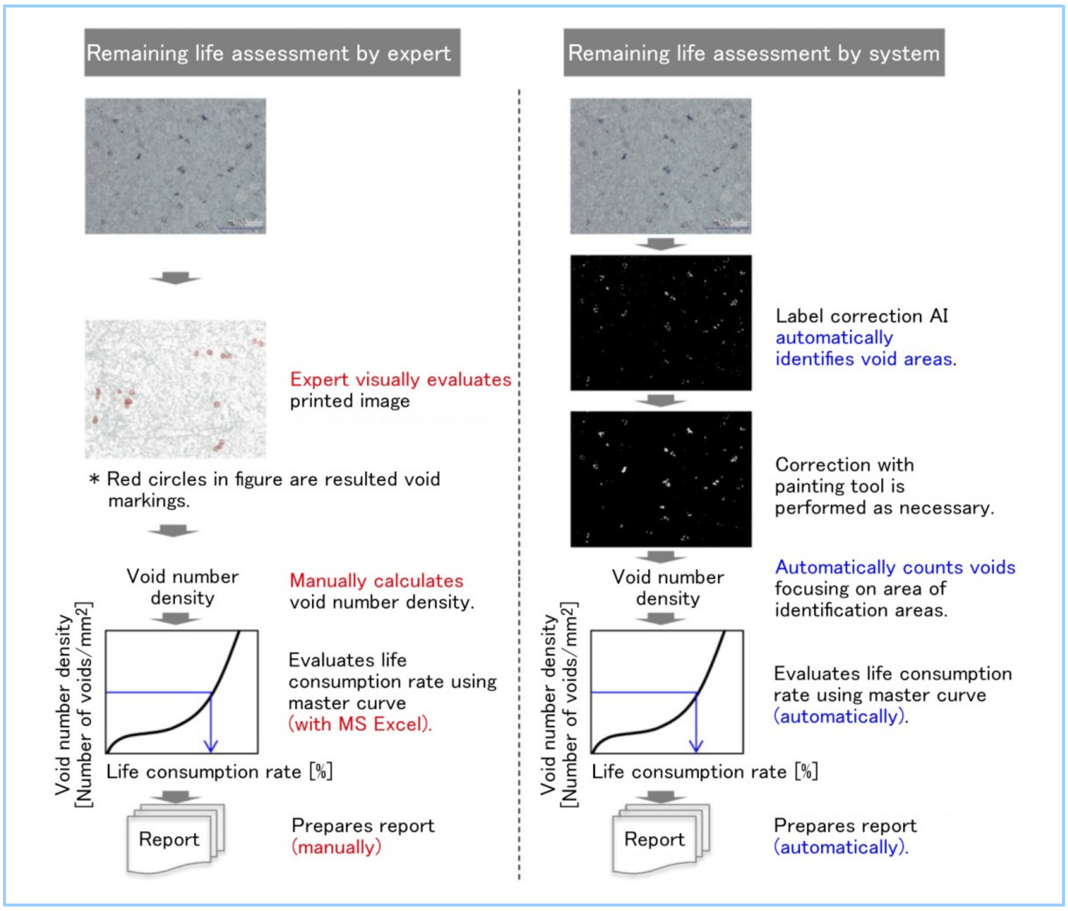

Figure 9 Comparison of work procedures of remaining life assessment by expert and by system (for high-strength ferritic steel)

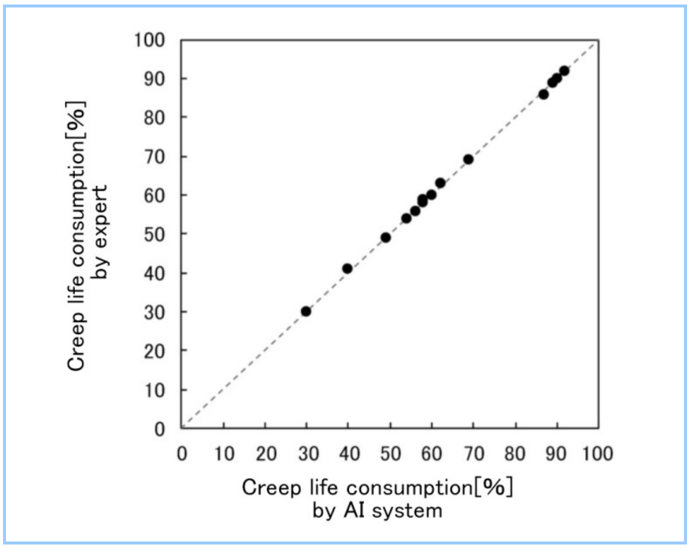

Figure 10 Verification result of life assessment accuracy (Grade 23 series steel (2.25Cr-1.6W-V-Nb))

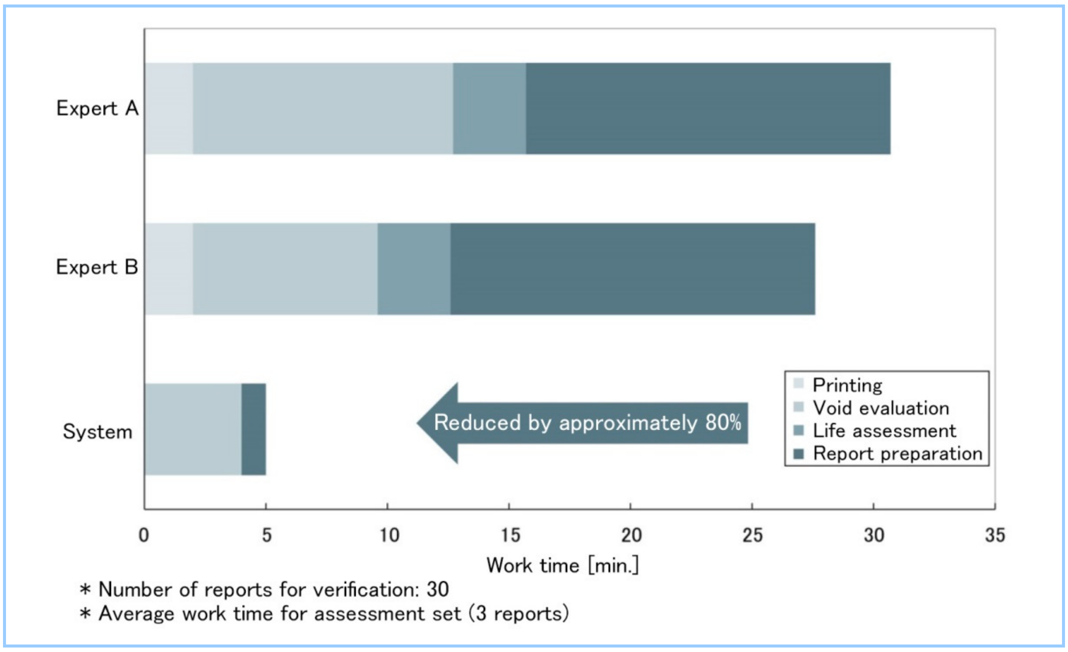

Figure 11 Effects of AI application to remaining life assessment work

6. Conclusion

This report introduced our initiative to provide better after-sales maintenance services for plant facilities we delivered to customers, without being dependent on experienced service technicians and experts. The problems of aging plant facilities and labor shortages mentioned in Chapter 1 are expected to become more serious in the future. In order to solve these social problems and improve our service capabilities, we will continue our efforts to promote the use of advanced technologies such as AI, and aim to provide services that will further satisfy our customers.

7. Acknowledgment

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