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Deterioration Score of Cold Forging Dies by Using Acoustic Emission Signals

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***Abstract* –It is generally difficult to estimate the degree of deterioration of forging dies, but it is necessary to prevent a large number of defective products. In this study, we propose a deterioration score in cold lateral forging using acoustic emission (AE) signals. From the analysis of the measured data, the transition of the signal from the initial state to the deteriorated state can be observed, and the transition can be numerically evaluated. In the evaluation, variational auto-encoder (VAE) is used for learning the initial distribution, and the deterioration score is calculated by the degree of deviation from the learned distribution. The AE cumulative maximum amplitude and AE cumulative count during the linearly increasing stress period for each forging shot are given to the input of the VAE encoder, and valid deterioration scores are obtained for multiple actual measurements.**

Keywords –Cold Forging, Die Deterioration, Acoustic Emission, Variational Auto-encoder, Sustainable Manufacturing.

I. INTRODUCTION

When metal processing is performed by cold forging [1], die deterioration is inevitable, and it is necessary to stop the process and replace the die before a large number of defective products are generated due to die breakage. Online monitoring is desired [2]. Although, it is not easy to estimate deterioration with conventional stress sensors or vibration sensors because stress and vibration changes are large in forging processes.

On the other hand, Acoustic Emission (AE) is a promising method to know the progress of minute defects in metal materials [3]. Since the AE signal represents a minute deformation of the die itself, it is a well-proven analysis method for estimating deterioration of static large scale equipment such as liquid tanks [4-6]. In cold forward forging, the possibility of crack estimation is shown from the distribution of AE amplitude and the number of event occurrences [7]. On the other hand, the operation of the press is complicated in cold lateral forging, so the AE signal is not simple either. However, if the mechanical operation timing of the press machine is appropriately determined and the AE signals due to the deterioration of dies (meaning the die and the punch in our case) are captured, it can be expected that the deterioration can be estimated.

In this study, we analyzed the measured AE signals generated by cold forging and calculated deterioration score by a neural network method (variational auto-encoder, VAE). The paper reports on the measurement method, analysis results, the scoring method, and effectiveness of its practical usage.

II. MEASUREMENTS

The main part of a typical cold lateral forging press is shown in Fig. 1, by which a bevel gear is forged from a spheroidized annealed material (SCM420) in one shot at intervals of about 4 seconds using a press machine (Komatsu L2C-1250L, 1,250t). The die and punch are customarily replaced due to deterioration after cumulative shots of up to around 50,000. Since the press operation is performed in unmanned manner, it is not possible to make a judgment on the way. Currently, deterioration judgments are made only at the time of suspension.

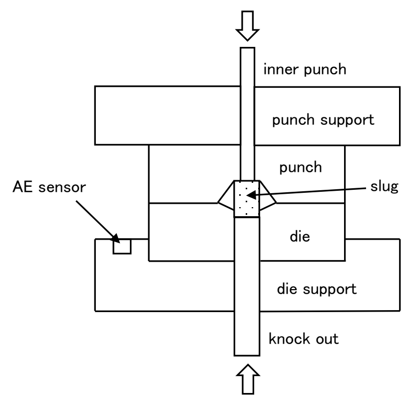

Fig. 1. Main components of the measured cold forging machine.

Displacement sensors (measuring the distance between the die and the punch) are attached to the moving part of the press machine, and load sensors (measuring the stress) are attached to the die and the knock out. An AE sensor (Shinwa Industries Inc FAEN-S150N, center frequency 150kHz resonance type) is attached to the die support. An AE signal preprocessing unit (Shinwa Industries Inc EDGE NODE EXPRESS DC) samples the AE signal at 10 MHz and outputs feature signals at 10 ms intervals so that relatively slow data acquisition equipment can collect them without omission. Specific feature signals are maximum amplitude, measured area under the rectified signal envelope (MARSE), root mean square (RMS), and counts (number of positive peaks).

Each forging cycle produces 400 preprocessor outputs as the feature signals come out at 10ms intervals. Impact sounds from the press machine are mixed in the signals as large noises. Removing them is not easy [8,9]. However, looking at the forging cycle in detail (Fig. 2), a bevel gear is manufactured by pushing the knock out while the upper and lower dies are closed by the load (Fig 1). While the dies are closed and forging is in progress, the impact noise of the processing machine is considered to be small. So, we start our AE measurement from 0.5s after the start of the press process, by then the die load is constant. And we stop the measurement at 1.1s when the load on the knock out reaches the peak. The total period of measurement is 0.6s, which corresponds to 60 preprocessor outputs.

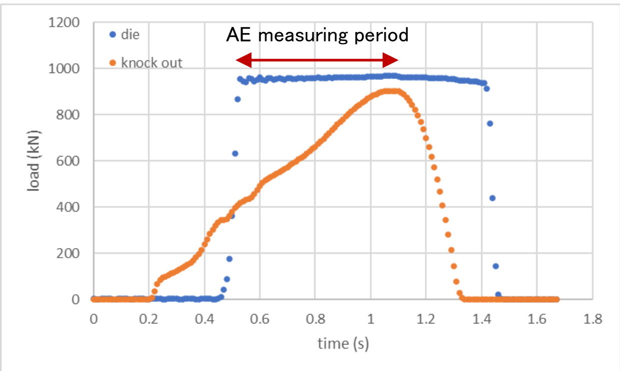

Fig. 2. Load changes on the die and the knoch out in an forging cycle.

As AE occurrences are stochastic in time, we recorded and processed only the aggregated values over the measurement period, although changes along each forging cycle may contain useful information. Specifically, the maximum amplitude illustrated in Fig. 3, MARSE, RMS, and counts for each preprocessing interval (Ti) are summed for each forging cycle. For example, the cumulative maximum amplitude is the value obtained by summing At in the figure for 60 time intervals (Ti).

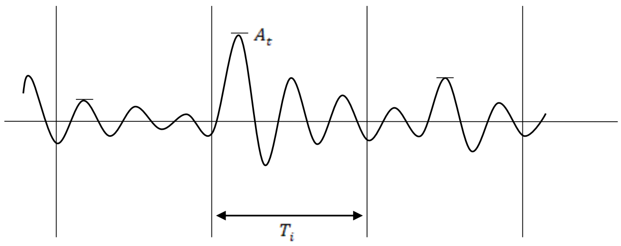

Fig. 3. . Example of AE signal and the feature value At (maximum amplitude) for each preprocessing time.

Three measured datasets (D1, D2, D3) were obtained on different dates with the same press machine and the dies for the same product. The number of shots for each dataset is about 23,000 (two days), 7,000 (one day) and 35,000 (three days), respectively. As the best variables expressing the deterioration of the dies, we used cumulative maximum amplitude and cumulative count from the preprocessing unit, accumulated for 0.6 seconds. These values are shown in Fig. 4 and 5 along the shot number (the shots are divided into four sections and colored to make the transition easier to catch in Fig. 6). Both values increase and decrease repeatedly. The overall time patterns of the values are similar, but there are some differences in the way they change. The MARSE and RMS from the preprocessing unit show almost the same changes as the maximum amplitude, while there exists differences mainly in the initial stages, which do not seem to be directly related to deterioration. Therefore, they are excluded from the following analysis.

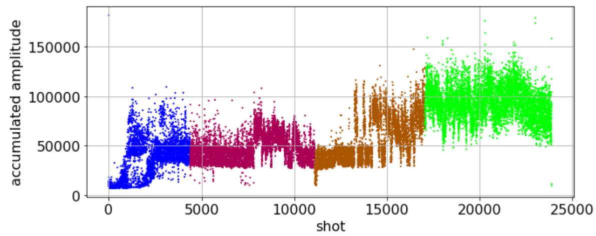

Fig. 4. An example of cumulative maximum amplitude (D1). Colors correspond to the transition in Fig. 6.

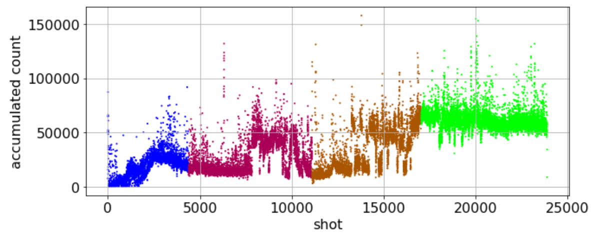

Fig. 5. An example of cumulative counts (D1). Colors correspond to the transition in Fig. 6.

Fig. 6 shows the two-dimensional distribution of the cumulative maximum amplitude vs the cumulative count. Since the original distribution has a large variation, Fig. 6 shows the moving average with the width of 20 shots. In the figure, streaking patterns show moving directions, and it can be clearly seen that the amplitude fluctuates up and down and the count fluctuates left and right.

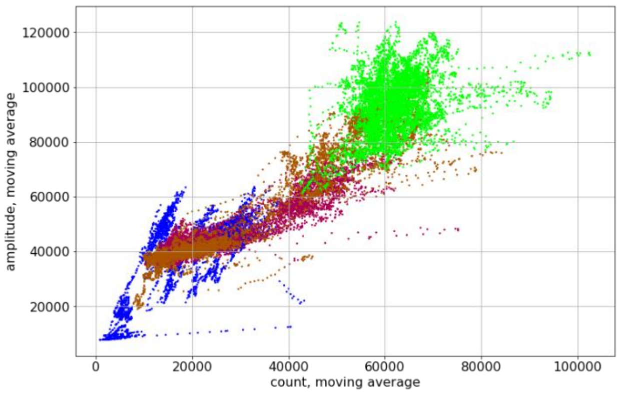

Fig. 6. 2D distribution of the cumulative maximum amplitude vs the cumulative count (D1).

Fig. 7 shows the distribution of three measurements overlaid on the same amplitude vs count map as Fig. 6. Blue (D2) and red (D3) points indicate measurements with the same dies on different days, and green (D1) indicate another measurement with different dies for the same product. There is a large gap between green points and red/blue points, which may be caused by noise, while the details are unknown. For all three datasets, it is distributed in the lower left at the initial stage of operation, and moves to the upper right while moving up, down, left, and right with the passage of time. It is unknown at what point and how much the dies were deteriorated, but roughly it moves to the upper right with the passage of time. Deterioration is assumed to be related to the amount of movement to the upper right. The sharp rises in red points seem to be abrupt changes, but the details are unknown.

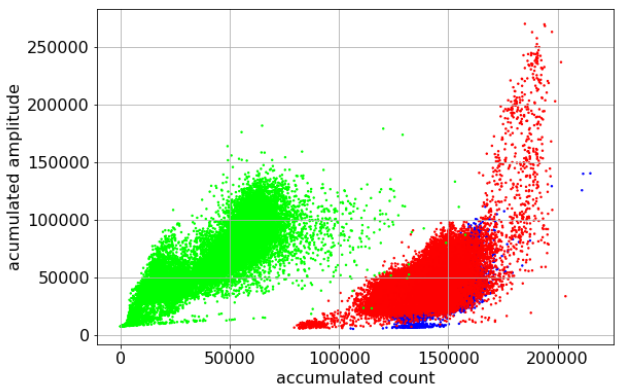

Fig. 7. 2D distribution of the three dataset (D1:green, D2:blue, D3:red).

III. VAE DETERIORATION SCORE

In order to quantify the amount of movement to the upper right in Fig. 7, it is necessary to determine the starting point and the inclination. As for the starting point, the origin is unsuitable because the distribution of red and blue are shifted. It is appropriate to define the distribution at the time when the initial deterioration is considered to be low or none and use the center of the distribution as the reference point. As for the inclination, it is not clear whether the slope of distribution inclination can be obtained in advance. Then, as in the case of the bearing anomaly scores [10], VAE [11] can be suitable means to calculate a deterioration score, which converts the initial distribution to the standard Gaussian distribution, and calculate the degree of deviation from that by measuring a Mahalanobis' distance from the origin.

As a brief explanation of VAE with a simple example in Fig. 8, it converts a training distribution (assumed to be the normal state distribution) of multidimensional measurement data (two-dimensional case in Fig. 8a) to a standard Gaussian distribution (zero mean and one standard deviation) on a reduced dimensional latent space (same dimensionality in Fig. 8b). The target dimensionality of the conversion may be specified to match the objective with keeping enough information of the trained distribution. Deviation from the normal state distribution can be measured by the distance from the origin.

Generally, in order to determine anomalies by learning only the normal state data without anomalous data, it is necessary to construct a scale that can discriminate normal or anomalous. For that purpose, it is appropriate to convert the normal state distribution into a fixed size, one stadard deviation is an appropriate choice. VAE would be the first candidate for it.

For example, if the distance from the origin is 3 (means 3σ distance) or more, the measured value occurs with a probability of 0.3% or less, and it can be judged as an anomaly. Actually, VAE may rotate the distribution axially during the dimensionality reduction, and may incompletely convert to the standard Gaussian distribution depending on the learning situation.

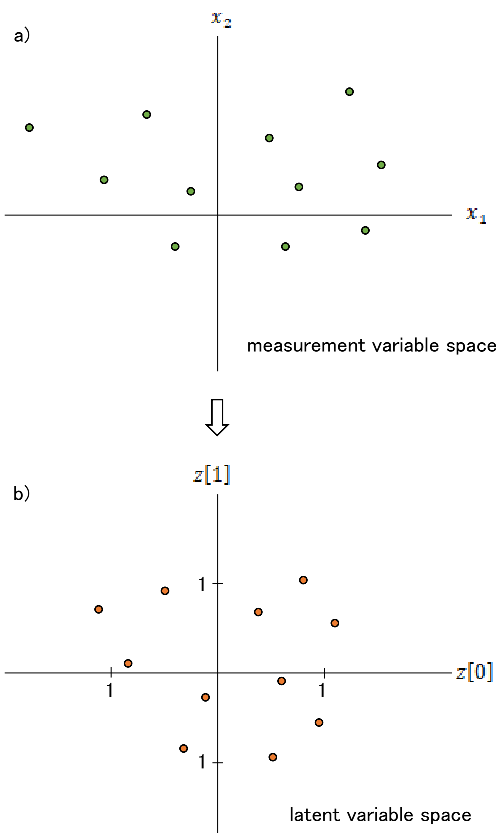

Fig. 8. Simplified illustration of VAE conversion. A two-dimensional distribution of measurements x1, x2 is converted to a standard Gaussian distribution on the latent space z[0], z[1].

Specifically, the distance from the distribution center is calculated as a vector distance with correcting the deviation σ_i for each axis in the VAE latent space (D dimension) as in Eq. (1) to obtain the score V_D. However, when the number of dimensions is redundant, this score may be overestimated. So, it is compensated by the redundancy degree Dcmps obtained by equations (2) and (3), where $f_i(n)$ is the input pattern when the latent variable i is 1, and N is the number of input values [10].

$$V_D = \sqrt{\frac{1}{D_{cmps}} \sum_{i=1}^{D} \left(\frac{z_i - \overline{z_i}}{\sigma_i}\right)^2}, \quad (1)$$

$$D_{cmps} = \frac{1}{D} \sum_{i=1}^{D} \sum_{j=1}^{D} R^2(f_i, f_j), \quad (2)$$

$$R(f_i, f_j) = \frac{1}{N} \sum_{n=1}^{N} f_i(n)\, f_j(n), \quad (3)$$

As the two VAE inputs (cumulative maximum amplitude and cumulative count) for each shot have large fluctuations, we used moving median of width of 40 points to smooth the inputs since the median keep the output with the existing value, although we used the moving average method in Fig. 6 to show the direction of changes.

Since the number of inputs is two, the latent space dimension is at most two dimensions, which makes the VAE structure as a simple configuration of two inputs and two latent variables. As the other hyperparameters of the VAE we adopted a two-layer structure (no intermediate layer), linear activation function, Adam optimizer, batch size of 50, and epoch number of 1,000.

Fig. 9-10 show the outline of the processing flow. We train the VAE encoder by putting two inputs for each shot repeatedly, and obtain the deterioration score calculated with equation (1) from the latent space variables z_0 and z_1. In Fig. 10, the training data period is shown in blue and the rest is shown in green.

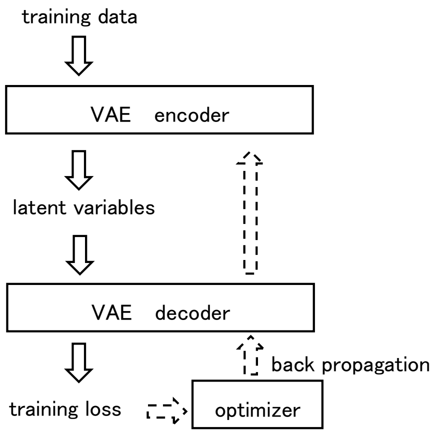

Fig. 9. Processing flow of the VAE.

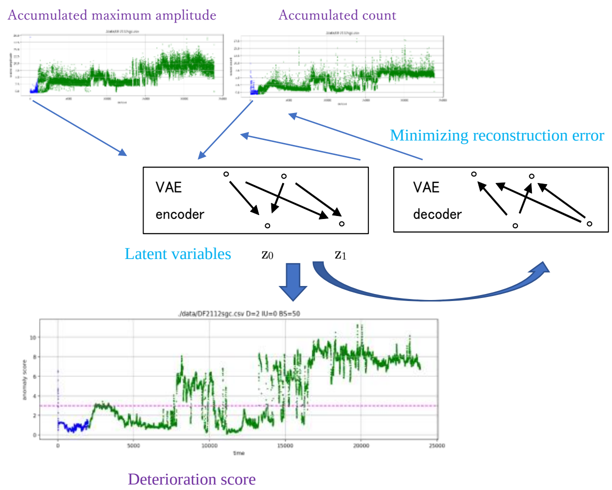

Fig. 10. Outline of the calculation of the deterioration score.

IV. RESULTS AND DISCUSSIONS

Fig. 11 shows an example of the latent space distribution when VAE training is performed for the data set D1. Although it cannot be regarded as the Gaussian distribution assumed by the VAE, it is converted into a distribution with the mean of zero and the variance of one. Fig. 12 shows the resultant latent space distribution for all shots including deterioration after the training period, and it can be seen that many points are far from the center of the training distribution. Figure 13 shows the deterioration score V_D, which gradually increases and does not return to the initial value range. It can be presumed that the change over time including deterioration is reliably represented by the score.

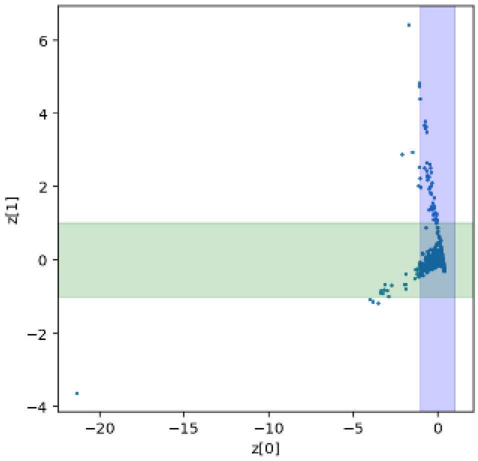

Fig. 11. Latent space distribution of 1,000 training shots. The horizontal and vertical axes are the first and the second latent variables.

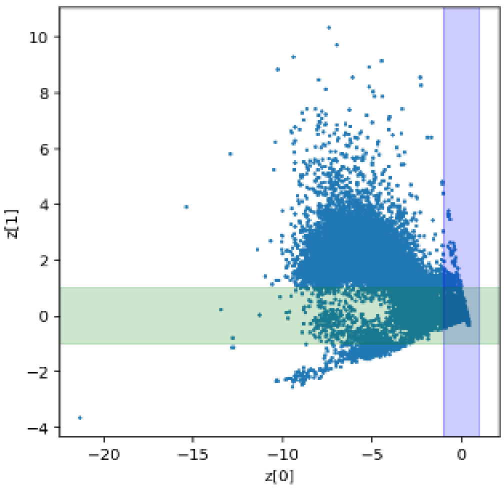

Fig. 12. Latent space distribution of all the measured shots. The horizontal and vertical axes are the first and the second latent variables.

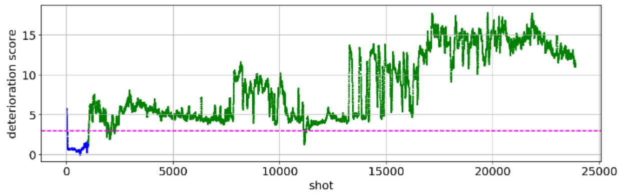

Fig. 13. Deterioration score of D1 (training period: 1,000shots).

Fig. 13 also shows that the deterioration score is more than 3σ (red dashed line) away from the training distribution for most of the time. Therefore, the deterioration may be overemphasized. When we expanded the training period to 2,000 shots as in Fig. 14, about the half of the shots have a low deterioration score, and the deterioration score intermittently shifts to a high level from the middle. It means that it is very important to set an appropriate training period for numerical judgments.

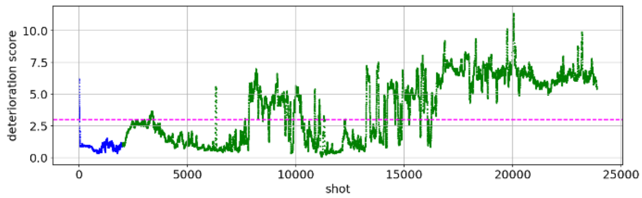

Fig. 14. Deterioration score of D1 (training period: 2,000shots).

Fig. 15 shows another example of the deterioration score of the dataset (D2). It jumps to a state with a high value intermittently like D1 at around the middle shot points. Fig. 16 shows the score of the dataset D3 which is the result of succeeding press operation at a later date using the same dies as D2. After the initial fluctuation, it keeps a low deterioration score for a long time, shows an upward trend at around 22,000 shots, and big swings at around 25,000 shots. Thereafter, the score moves to larger values, which may be an indication of permanent deterioration.

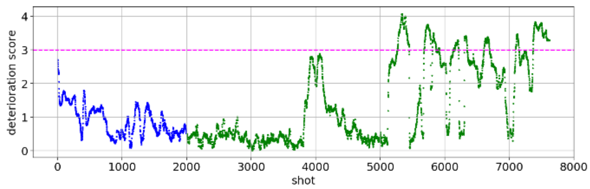

Fig. 15. Deterioration score of D2 (training period: 2,000shots).

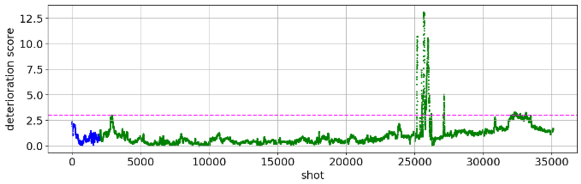

Fig. 16. Deterioration score of D3 (training period: 2,000shots).

V. CONCLUSIONS AND FUTURE WORK

We propose a deterioration score for judging the deterioration of dies in the cold lateral forging, and have shown that the score is effective. The score is calculated as the degree of deviation from the trained distribution based on the Mahalanobis' distance in the VAE latent space using the cumulative AE maximum amplitude and the cumulative AE count of each press shot when the press stress linearly increases.

Since it is currently unknown at what point the dies are damaged, it is unclear to what extent the calculated deterioration score corresponds to the actual deterioration. And also, it is not easy to use it as an absolute deterioration index because the defect judgment of the dies is affected by the accuracy required for the product to be forged. However, it can be expected to approach the prediction of the life of dies by gaining experience with the actual productions.

VI. ACKNOWLEDGMENT

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