Prediction of metal temperature by microstructural features in creep exposed austenitic stainless steel with sparse modeling

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ABSTRACT
This study proposes a framework to estimate the metal temperature from an optical micrograph of metals by using a machine learning approach. Specifically, 38 image statistical parameters such as area, contour, and circularity are calculated for the precipitate region determined through optical microscopy. Sparse modeling is then conducted to build a statistical model to estimate the Larson-Miller parameter (LMP), which is generally used in the evaluation of creep strength. This allows for the prediction of the metal temperature from the optical micrographs. The prediction performance of the proposed method is analyzed by applying it to KA-SUS304J1HTB (18Cr-9Ni-3Cu-Nb-N steel), reported in the NIMS Creep Data Sheets No. 56A and No. M-11. Consequently, temperature prediction is successfully achieved for unknown data with an error within ±10°C.

1. Introduction

Austenitic stainless steels are widely used in power plants because of their high creep strength. However, they have been reported to experience premature failure occurred in the steels [1,2]. A new evaluation method was proposed to determine the creep strength of high-strength stainless steel considering premature failure [3]. In addition to creep strength evaluation, the residual life assessment of high-strength stainless steels is important for the safe operation of aging power plants. In actual power plants, the metal temperature, stress, and operating time are required to predict the residual life of components. Normally, in actual power plants, stress of pipe, and tube can be calculated, considering internal pressure by steam. The operating time is usually known. However, in some cases, the metal temperatures of the pipe and tube are unknown because steam temperature is different depending on part of pipe and tube in actual power plants. Furthermore, it is difficult to measure the metal temperature of each tube by thermocouple because a large number of tubes are installed in actual power plants [4]. Therefore, methods to know actual metal temperature of a serviced tube are needed to predict the residual creep life. The dislocation structure and the precipitates generally change during creep exposure, depending on the temperature and time. Therefore, the changes in the microstructure, such as dislocations and precipitates, can be utilized to predict the metal temperature. For example, Matsumura et al. [4] and Thuy Dang Nguyen et al. [5] reported that the metal temperature of 2.25Cr-1Mo steel can be predicted by measuring the width of the precipitate-free zone. In many cases, industry experts for steel observe the microstructures and predict the metal temperature.

Specifically, the features of the precipitate region determined from an optical micrograph can be calculated via image processing, and the regression to the Larson-Miller parameter (LMP), which is generally...
used in creep strength evaluation, considered by using these features as the inputs. The features obtained from the precipitate area include the size, area fraction, and number density of the precipitates. Based on the previous studies [4] that analyzed the correlation between these features and the LMP, the precipitate feature is considered to be crucial for estimating the metal temperature. However, multivariate analysis of such features has not been well discussed. In this study, a comprehensive set of image statistical parameters such as area, contour, circularity, and distance between the regions, is constructed for a total of 38 feature dimensions. These features are considered to be important for the LMP regression, and the framework of sparse modeling is established. To verify the effectiveness of the proposed method, it is applied to KA-SUS304J1HTB (18Cr-9Ni-3Cu-Nb-N steel), reported in the NIMS Creep Data Sheets No. 56A [6] and No. M-11 [1], to analyze the fitting and prediction performances. Consequently, this study successfully predicts the temperature for unknown data with an error within ± 10 °C.

2. Dataset

2.1. NIMS creep data sheet

KA-SUS304J1HTB (18Cr-9Ni-3Cu-Nb-N steel) was used in this study. The chemical composition, heat treatment conditions, and creep data of the steel used in this study have been reported in the NIMS Creep Data Sheet No. 56A [6] and No. M-11 [1]. The microstructure of creep-rupture samples was observed through optical microscopy. The specimens for observation were cut longitudinally parallel to the stress direction, polished on emery papers and on buffing cloths with paste, followed by etching. Etching was performed electrolytically for 25–145 s at 0.5–1.0 V in a solution of 5% hydrochloric acid and ethanol at room temperature. Figure 1 shows an example of a creep-rupture sample. The microstructure of the grip and gauge portions of the creep-rupture samples can be observed. The microstructure obtained from the grip portion indicates that no stress is applied on the grip portion in the aged samples. As described in Section 4, the data from the grip portion are used to train the model, and the data from the gauge portion are used to evaluate (test) the performance of the trained model. The detailed temperature, time, and image conditions are described in Section 4.

2.2. Larson-Miller parameter

The LMP is one of the parameters used to convert the temperature and the time of materials [7]. The LMP is commonly used to extrapolate the strength of a creep-rupture sample or to estimate the temperature of a metal that has been heated for a long time. This study overcomes the issue of estimating the temperature from the creep-rupture samples that have been heat-treated for a long time. Considering the absolute temperature of the material $T$ [K] and the rupture time $t_r$ [h] as the data, the LMP is defined as follows:

$$LMP = T(\log t_r + C).$$

Constant C is a regulating parameter in the LMP; in this study, it is set to $C = 15$.

3. Method

Figure 2 shows the workflow for image analysis in this study. At first, we pick and mark the precipitates in the optical micrograph. From the marking image, we quantify with the image features. Bolasso [8], a type of sparse modeling, is utilized to perform feature selection and regress these features to the LMP.

3.1. Marking the precipitates

In the steel studied, $M_{23}C_6$, NbC, Z-phase, Cu-phase, and $\sigma$-phase are precipitated during creep exposure [1]. The size and area fraction of $\sigma$-phase clearly increases during creep exposure [1], indicating that change of $\sigma$-phase is very sensitive to temperature. Therefore, we focused on the $\sigma$-phase. The optical micrographs were taken at x400 magnification, using an optical microscope (MICROPHOT-FXA, Nikon, Japan) equipped with a digital camera (EOS-1 Ds, Canon, Japan). The sizes of NbC, Z-phase, and Cu-phase are less than 100 nm even after creep exposure [1,2]. Therefore, these precipitates are not visible in optical micrograph due to low magnification. Some of $M_{23}C_6$ can be visible in optical micrograph because the size of $M_{23}C_6$ is less than 1µm after creep exposure [1]. All of $\sigma$-phase can be seen in optical micrograph since the mean size is from 1µm to 7µm depending on temperature and time [1]. The shape of $M_{23}C_6$ is massive although that of $\sigma$-phase is plate or needle. Consequently, we distinguished $\sigma$-phase from $M_{23}C_6$ based on size and shape of precipitates in optical micrograph.

![Figure 1. Example of a creep-rupture sample.](image-url)
3.2. Feature extraction

Feature extraction utilizes an optical micrograph which is identified regions as the precipitates. Figure 3 shows an example of the feature extraction from a marked precipitate region. From the selected regions, the size, contour length, and circularity of each region and the distance between adjacent regions are computed. In this study, the distance between two neighboring regions of the region of interest is calculated. In Figure 3, the patch image of the sample shows that the regions in red are marked, the green lines represent the outlines of the areas, and the blue lines represent the adjacencies of the areas. Each value is converted from the pixel scale to the real scale value, which is recorded at the time of measurement. The circularity of the region is calculated by the following equation:

$$\text{Circularity} = \frac{4\pi S}{L^2}$$

(2)

where $S$ is the size of the region and $L$ is the contour length of the region. Based on the values of these parameters of the target regions in the image, five statistics of mean, variance, median, minimum, and maximum were calculated and used as features.

In this study, two classes of features are extracted corresponding to the targeted regions. The first class contains the statistical information for all identified regions, and the other contains the statistical information corresponding to the regions that are selected as the top 20% based on the largest size. A list of the specific features is presented in Table 1. The extracted features are the 38 dimensions.

Because some studies have reported that precipitates increase in size and become larger corresponding to the temperature and time in images of the materials exposed to high temperatures, the LMP can be potentially regressed by using these parameters. However, because it is difficult to determine the features that are effective for the regression of the LMP parameters beforehand, a statistical framework called sparse modeling is used, as explained in the following sections, to construct a statistical model to regress the LMP while performing feature selection.

3.3. Regression of LMP by sparse modeling

This section describes a sparse modeling framework for regressing the LMP using the constructed 38-dimension features. The linear regression model is
Table 1. Description of image features.

| Index | Feature name        | Description                                                                 |
|-------|---------------------|-----------------------------------------------------------------------------|
| 1     | Num area            | Number of precipitates                                                      |
| 2     | Total size          | Total size of the region for precipitates                                   |
| 3     | Total rate          | Percentage of the precipitate area in the optical micrograph                |
| 4     | Size mean           | Average size of the precipitate in the optical micrograph                   |
| 5     | Size variance       | Variance of size for the precipitate in the optical micrograph              |
| 6     | Size median         | Median of size for the precipitate in the optical micrograph                |
| 7     | Size min            | Minimum size for the precipitate in the optical micrograph                  |
| 8     | Size max            | Maximum size for the precipitate in the optical micrograph                  |
| 9     | Arc mean            | Average contour length for the precipitate in the optical micrograph        |
| 10    | Arc variance        | Variance of contour length for the precipitate in the optical micrograph    |
| 11    | Arc median          | Median of contour length for the precipitate in the optical micrograph      |
| 12    | Arc min             | Minimum of contour length for the precipitate in the optical micrograph     |
| 13    | Arc max             | Maximum contour length for the precipitate in the optical micrograph        |
| 14    | Cir mean            | Average of circularity for the precipitate                                  |
| 15    | Cir variance        | Variance of circularity for the precipitate                                 |
| 16    | Cir median          | Median of circularity for precipitate                                       |
| 17    | Cir min             | Minimum of circularity for the precipitate                                  |
| 18    | Cir max             | Maximum of circularity for the precipitate                                  |
| 19    | Edge mean           | Average of distance between neighboring precipitates                         |
| 20    | Edge variance       | Variance of distance between neighboring precipitates                        |
| 21    | Edge median         | Median of distance between neighboring precipitates                          |
| 22    | Edge min            | Minimum of distance between neighboring precipitates                          |
| 23    | Edge max            | Maximum of distance between neighboring precipitates                          |
| 24    | Size mean(20%)      | Average size of the top 20% of the total                                    |
| 25    | Size variance(20%)  | Variance of size of the top 20% of the total                                 |
| 26    | Size median(20%)    | Median of size of the top 20% of the total                                   |
| 27    | Size min(20%)       | Minimum of size of the top 20% of the total                                  |
| 28    | Size max(20%)       | Maximum of size of the top 20% of the total                                  |
| 29    | Arc mean(20%)       | Average contour length of the top 20% of the total                           |
| 30    | Arc variance(20%)   | Variance of contour length of the top 20% of the total                      |
| 31    | Arc median(20%)     | Median of contour length of the top 20% of the total                         |
| 32    | Arc min(20%)        | Minimum of contour length of the top 20% of the total                        |
| 33    | Arc max(20%)        | Maximum of contour length of the top 20% of the total                        |
| 34    | Cir mean(20%)       | Average of circularity for the top 20% of the total                          |
| 35    | Cir variance(20%)   | Variance of circularity for the top 20% of the total                         |
| 36    | Cir median(20%)     | Median of circularity for the top 20% of the total                           |
| 37    | Cir min(20%)        | Minimum of circularity for the top 20% of the total                          |
| 38    | Cir max(20%)        | Maximum of circularity for the top 20% of the total                          |

used to predict the LMP from these features. Consider that the feature to be fed to the linear regression model is vector \( x = (x_1, x_2, \ldots, x_P) \) with \( P = 38 \) dimensions and let the weight parameters corresponding to each dimension be \( w = (w_1, w_2, \ldots, w_P) \). The regression to the LMP is considered based on these inputs:

\[
y(x; w) = w_0 + \sum_{p=1}^{P} w_p x_p,
\]

where \( P \) denotes the dimension of the feature in \( x \), and \( w_0 \) is a constant term. The feature input data extracted from \( N \) images are denoted by \( X = \{x_1, x_2, \ldots, x_N\} = \{x_n\}_{n=1}^{N} \), and the output of the regression model obtained from each feature vector as the LMP is denoted as \( Y = \{y_1, y_2, \ldots, y_N\} = \{y_n\}_{n=1}^{N}, y_n = y(x_n; w) \).

For this linear regression model, a sparse modeling framework is used to simultaneously select the important features and regress the LMP. Specifically, LASSO is considered to set the weight parameter, \( w \). In LASSO, the weight parameter, \( w \), which minimizes the objective function, \( E(w) \), is identified.

\[
E(w) = \frac{1}{2} \sum_{n=1}^{N} (y_n - y_n)^2 + \lambda \sum_{p=1}^{P} |w_p|
\]

The first term represents the degree of fitting of the linear regression model to the LMP data, and the second term represents the regularization term for dropping features with a low contribution. The hyperparameter, \( \lambda \), is used to adjust these balances. By adding this regularization term, some elements such as \( w_i \) of \( w \) are more likely to become 0, which makes it easier to select a sparse solution. When the weight, \( w_p \), is 0, the \( p \)-th feature does not contribute to the output, \( y(x; w) \); this feature can thus be considered as the result that is not selected.

Although the feature selection through LASSO is a method used in various fields, LASSO is sensitive to the strength of the regularization term and the noise of the given data. Moreover, the estimated weight parameter, \( w \), can vary significantly even for minor noise. To overcome this issue, Bolasso, a sparse modeling method that incorporates the bootstrapping technique [9], is considered as an alternative to the LASSO method [8, 10].

4. Experiments

To verify the effectiveness of the proposed method, the exposure temperature is estimated using the LMP from the creep-rupture microstructure images. It is
possible to estimate the temperature by using the LMP because the operating time is typically known in actual power plants. The model was constructed using 13 sample patterns at different temperatures and times from the dataset. Several images were obtained for each sample from the creep-rupture specimen measured at different locations, such as the grip and gauge portions, with a field of view of 362.3 μm × 241.7 μm. Therefore, 94 images of the screw part from 13 sample patterns were used to train the regression model. The details are summarized in Table 2. To evaluate the constructed model, the microstructure images of the gauge portion in five out of 13 samples were considered as test data. The conditions in the test data are also summarized in Table 3. To build the model, the features were standardized to ensure that each feature of the training data has a mean of 0 and a variance of 1.

### 4.1. Feature selection

We considered regressing the LMP using the 38 defined features. To this end, the following four methods were considered:

1. Regression of the LMP without feature selection using all 38 features. [ALL]
2. Regression of LMP with feature selection for all 38 features. [FS]
3. Regression of LMP without feature selection using 15 features defined for 20% representative regions. [ALL(20%)]
4. Regression of LMP with feature selection for 15 features defined for 20% representative regions. [FS(20%)]

The results of the estimation of the LMP from the training data obtained from the above-mentioned four methods are shown in Figure 4. For the hyperparameter, λ, in the feature selection in [FS] and [FS (20%)], the value with the smallest error was adopted in the 10-fold cross-validation method with the data being used for training. The coefficients of determination $R^2$ for the four methods were 0.97, 0.92, 0.90, and 0.87, respectively, which indicates that these models could fit the LMP with high accuracy.

The results and the coefficients of the feature selection by the four methods are presented in Figure 5. The red areas indicate that the coefficients take positive values, while the blue areas indicate that the coefficients have negative values. A white area indicates that the variable is not used in the regression. From the results of the feature selection method [FS], it is observed that the regression does not use the features of the representative region at 20%, and only uses the features of the entire region. One reason for this is that the population parameter is more stable in the entire region when performing the statistical calculations, due to which, it is a stable feature quantity. Conversely, when compared with the feature selection method [FS (20%)] which targets 20% of the representative area, the features that are commonly selected can be observed. Specifically, the mean value (size mean) in the region and the mean value (arc mean) in the contour were selected, and the signs of the coefficients were also equivalent. The results can vary depending on whether a large or small precipitate is emphasized.

### 4.2. Model evaluation by test data

Lastly, Table 4 shows the results of the prediction of the temperature via the LMP using the test data by applying the regression model constructed on the basis of the four methods. All methods were observed to have a prediction error of approximately 10 °C when comparing the averages of the errors. Because the dataset used in this study includes temperatures at 50 °C intervals, all methods were considered to be sufficiently predictive. Among the four methods, [FS (20%)] exhibited the smallest root mean squared error, mean error, and standard deviation. These results indicate that only large precipitates can be intuitively identified in the micrograph by visually characterizing the temperature and time conditions. By calculating the features from the top 20% of the
Figure 4. Regression results for LMP. The horizontal axis represents the measured value, and the vertical axis represents the estimated value.

Figure 5. Feature selection results and parameter values in LMP regression.

Table 4. Temperature prediction results for test data.

|      | 1     | 2     | 3     | 4     | 5     | RMSE | Ave. residual | Std. residual |
|------|-------|-------|-------|-------|-------|------|---------------|---------------|
| True | 650.0 [°C] | 750.0 [°C] | 750.0 [°C] | 650.0 [°C] | 700.0 [°C] | 9.69 | 3.26 | 10.20 |
| [All] | 658.0 [°C] | 749.1 [°C] | 737.3 [°C] | 662.2 [°C] | 709.7 [°C] | 17.7 | -7.24 | 15.12 |
| [FS] | 659.4 [°C] | 732.9 [°C] | 715.8 [°C] | 655.9 [°C] | 708.8 [°C] | 13.1 | -7.32 | 12.20 |
| [All(20%)] | 658.9 [°C] | 732.1 [°C] | 729.1 [°C] | 644.8 [°C] | 698.4 [°C] | 8.51 | -1.00 | 9.45 |
region instead of all precipitates, it is assumed that the statistically stable features are obtained for the LMP prediction. From this experiment, the temperature can be predicted from the micrograph of the gauge portion with high accuracy by using the model constructed from the micrograph of the grip portion. This indicates that the microstructural features of the grip and gauge portions are almost equivalent under the same conditions, as shown in the literature [1].

5. Discussion

In this section, we discuss about the proposed method and the results. In the steel studied, $\text{M}_{23}\text{C}_{6}$, NbC, Z-phase, Cu-phase, and $\sigma$-phase can affect creep strength. Therefore, in order to predict creep strength from image feature, the information of type of precipitate, chemical composition, crystal structure and so on may be needed. However, in this study, our aim is to predict the metal temperature by microstructural features. In this case, if we can find a measure that has strong relation to temperature and time, it is possible to predict metal temperature by only the measure. The $\sigma$-phase was a good measure to predict the metal temperature in the steel studied because the size and area fraction of the $\sigma$-phase clearly increases with increasing time and temperature [1]. In the case of 2.25Cr-1Mo steel, the precipitate-free zone was a good measure to predict metal temperature [4,5].

Some features as the size and shape of the precipitates are selected by applying the feature selection. This result would capture the relationship between the $\sigma$-phase and the temperature. Although in Appendix A, some of the features have high correlation with each other, we consider that the feature selection process chooses the most important subset of features for metal temperature prediction.

On the other hand, the verification of the versatility of the proposed method is an issue that must be addressed for expanding its practical application. This experiment attempted to estimate the temperature for a specific metal microstructure of a specific material; however, there are various cases that are actually used in the field. Therefore, it is important to verify whether the temperature can be predicted for other metal microstructures and for other materials. Furthermore, analyzing the limits of the temperature prediction by the proposed method and quantitatively presenting the confidence level of the results by incorporating Bayesian and other frameworks can effectively improve the reliability of the proposed method. It is also known that changes in the metal microstructure behave differently at high and low temperatures, such as above 800°C, and the development of a model that can adequately handle the nonlinear relationship is challenging.

To overcome these issues, the automatic detection of the precipitate regions must be promoted. Currently, the regions of interest are decided by marking. This process takes more than an hour per image depending on the sample, making the data collection process very expensive. Therefore, by modeling the process of marking and by automatically or semiautomatically detecting the precipitate regions, the versatility of the proposed method can be efficiently verified and the model can be refined such that the above-mentioned issues are overcome.

6. Conclusion

This study aimed to predict the temperature via the LMP by using the microstructural features. By calculating the features from the micrograph according to the regions of the precipitates, a model was constructed to predict the LMP, which is a state parameter containing the temperature and time of the sample. Although the constructed model was simple, it was able to predict the temperature of the test data with high accuracy. As our future problems, it is important to verify the versatility of our proposed method for structural materials, and to develop the automatic detection algorithm of the precipitate regions from micrograph.

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Appendix A. Correlation of the features extracted in this study

We checked the correlation of the features extracted in this study. Figure A1 shows correlation matrix of the features extracted in this study. The color in the figure indicates correlation coefficient. Correlation coefficient has a value in the range of 1 to −1. In Figure A1, a high value is red, and a low value is blue. If the coefficient is close to 0, the color is white.

Figure A1. Correlation matrix of the features extracted in this study.